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# Multisensor data fusion: A review of the state-of-the-art

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ABSTRACT

There has been an ever-increasing interest in multi-disciplinary research on multisensor data fusion technology, driven by its versatility and diverse areas of application. Therefore, there seems to be a real need for an analytical review of recent developments in the data fusion domain. This paper proposes a comprehensive review of the data fusion state of the art, exploring its conceptualizations, benefits, and challenging aspects, as well as existing methodologies. In addition, several future directions of research in the data fusion community are highlighted and described.



## 1. Introduction

Multisensor data fusion is a technology to enable combining information from several sources in order to form a unified picture. Data fusion systems are now widely used in various areas such as sensor networks, robotics, video and image processing, and intelligent system design, to name a few. Data fusion is a wide ranging subject and many terminologies have been used interchangeably. These terminologies and ad hoc methods in a variety of scientific, engineering, management, and many other publications, shows the fact that the same concept has been studied repeatedly. The focus of this paper is on multisensor data fusion. Thus, throughout this paper the terms data fusion and multisensor data fusion are used interchangeably.

The data fusion research community have achieved substantial advances, especially in recent years. Nevertheless, realizing a perfect emulation of the data fusion capacity of the human brain is still far from accomplished.

This paper is an endeavor to investigate the data fusion task, including its potential advantages, challenging aspects, existing methodologies, and recent advances. In particular, discussion of the existing data data fusion methods relies on a data-centric taxonomy, and explores each method based on the specific data-related challenging aspect(s) addressed. We also present less-studied issues pertinent to data fusion, and discuss future avenues of research in this area. While several general [1–3] and specific [4–8] reviews of the data fusion literature exist; this paper is intended to provide the reader with a generic and comprehensive view of contemporary data fusion methodologies, as well as the most recent developments and emerging trends in the field. The bulk of data fusion research has been dedicated to problems associated with the first level of the Joint Directors of Laboratories (JDL) model [3]. As work on low-level fusion becomes well established and approaches maturity, research on high level fusion tasks is gaining more attention. A discussion of new developments on high level fusion methodologies may be insightful; nonetheless, as the focus of this paper is on low level fusion, such presentation is left to a future work.

The rest of this paper is organized as follows: in Section 2 popular definitions, conceptualizations, and purposes, as well as the major benefits of data fusion, are discussed. The challenging problems pertaining to performing data fusion are described in Section 3. Section 4 provides a discussion of data fusion methodologies based on their data treatment approach. In Section 5, various new avenues of research, as well as emerging trends in the data fusion community, are provided. Finally, Section 6 presents the concluding remarks for this paper.

## 2. Multisensor data fusion

Many definitions for data fusion exist in the literature. Joint Directors of Laboratories (JDL) [9] defines data fusion as a "multi-level, multifaceted process handling the automatic detection, association, correlation, estimation, and combination of data and information from several sources." Klein [10] generalizes this definition, stating that data can be provided either by a single source or by multiple sources. Both definitions are general and can be applied in different fields including remote sensing. In [11], the authors present a review and discussion of many data fusion definitions. Based on the identified strengths and

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weaknesses of previous work, a principled definition of information fusion is proposed as: "Information fusion is the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making". Data fusion is a multidisciplinary research area borrowing ideas from many diverse fields such as signal processing, information theory, statistical estimation and inference, and artificial intelligence. This is indeed reflected in the variety of the techniques presented in Section 4.

Generally, performing data fusion has several advantages [12,2]. These advantages mainly involve enhancements in data authenticity or availability. Examples of the former are improved detection, confidence, and reliability, as well as reduction in data ambiguity, while extending spatial and temporal coverage belong to the latter category of benefits. Data fusion can also provide specific benefits for some application contexts. For example, wireless sensor networks are often composed of a large number of sensor nodes, hence posing a new scalability challenge caused by potential collisions and transmissions of redundant data. Regarding energy restrictions, communication should be reduced to increase the lifetime of the sensor nodes. When data fusion is performed during the routing process, that is, sensor data is fused and only the result is forwarded, the number of messages is reduced, collisions are avoided, and energy is saved.

Various conceptualizations of the fusion process exist in the literature. The most common and popular conceptualization of fusion systems is the JDL model [9]. The JDL classification is based on the input data and produced outputs, and originated from the military domain. The original JDL model considers the fusion process in four increasing levels of abstraction, namely, object, situation, impact, and process refinement. Despite its popularity, the JDL model has many shortcomings, such as being too restrictive and especially tuned to military applications, which have been the subject of several extension proposals [13,14] attempting to alleviate them. The JDL formalization is focused on data (input/output) rather than processing. An alternative is Dasarathy's framework [15] that views the fusion system, from a software engineering perspective, as a data flow characterized by input/output as well as functionalities (processes). Another general conceptualization of fusion is the work of Goodman et al. [16], which is based on the notion of *random sets*. The distinctive aspects of this framework are its ability to combine decision uncertainties with decisions themselves, as well as presenting a fully generic scheme of uncertainty representation. One of the most recent and abstract fusion frameworks is proposed by Kokar et al. [17]. This formalization is based on category theory and is claimed to be sufficiently general to capture all kinds of fusion, including data fusion, feature fusion, decision fusion, and fusion of relational information. It can be considered as the first step towards development of a formal theory of fusion. The major novelty of this work is the ability to express all aspects of multi-source information processing, i.e., both data and processing. Furthermore, it allows for consistent combination of the processing elements (algorithms) with measurable and provable performance. Such formalization of fusion paves the way for the application of formal methods to standardized and automatic development of fusion systems.

## 3. Challenging problems of multisensor data fusion

There are a number of issues that make data fusion a challenging task. The majority of these issues arise from the data to be fused, imperfection and diversity of the sensor technologies, and the nature of the application environment as following:

- *Data imperfection:* data provided by sensors is always affected by some level of impreciseness as well as uncertainty in the measurements. Data fusion algorithms should be able to express such imperfections effectively, and to exploit the data redundancy to reduce their effects.
- *Outliers and spurious data: the* uncertainties in sensors arise not only from the impreciseness and noise in the measurements, but are also caused by the ambiguities and inconsistencies present in the environment, and from the inability to distinguish between them [18]. Data fusion algorithms should be able to exploit the redundant data to alleviate such effects.
- *Conflicting data:* fusion of such data can be problematic especially when the fusion system is based on evidential belief reasoning and Dempster's rule of combination [19]. To avoid producing counter-intuitive results, any data fusion algorithm must treat highly conflicting data with special care.
- *Data modality:* sensor networks may collect the qualitatively similar (homogeneous) or different (heterogeneous) data such as auditory, visual, and tactile measurements of a phenomenon. Both cases must be handled by a data fusion scheme.
- *Data correlation:* this issue is particularly important and common in distributed fusion settings, e.g. wireless sensor networks, as for example some sensor nodes are likely to be exposed to the same external noise biasing their measurements. If such data dependencies are not accounted for, the fusion algorithm, may suffer from over/under confidence in results.
- *Data alignment/registration:* sensor data must be transformed from each sensor's local frame into a common frame before fusion occurs. Such an alignment problem is often referred to as sensor registration and deals with the calibration error induced by individual sensor nodes. Data registration is of critical importance to the successful deployment of fusion systems in practice.
- *Data association:* multi-target tracking problems introduce a major complexity to the fusion system compared to the single-target tracking case [20]. One of these new difficulties is the data association problem, which may come in two forms: measurement-to-track and track-to-track association. The former refers to the problem of identifying from which target, if any, each measurement is originated, while the latter deals with distinguishing and combining tracks, which are estimating the state of the same real-world target [3].
- *Processing framework:* data fusion processing can be performed in a centralized or decentralized manner. The latter is usually preferable in wireless sensor networks, as it allows each sensor node to process locally collected data. This is much more efficient compared to the communicational burden required by a centralized approach, when all measurements have to be sent to a central processing node for fusion.
- *Operational timing:* the area covered by sensors may span a vast environment composed of different aspects varying in different rates. Also, in the case of homogeneous sensors, the operation frequency of the sensors may be different. A well-designed data fusion method should incorporate multiple time scales in order to deal with such timing variations in data. In distributed fusion settings, different parts of the data may traverse different routes before reaching the fusion center, which may cause out-of-sequence arrival of data. This issue needs to be handled properly, especially in real-time applications, to avoid potential performance degradation.
- *Static vs. dynamic phenomena:* the phenomenon under observation may be time-invariant or varying with time. In the latter case, it may be necessary for the data fusion algorithm to incorporate a recent history of measurements into the fusion process [21]. In particular, data freshness, i.e., how quickly data sources capture changes and update accordingly, plays a vital

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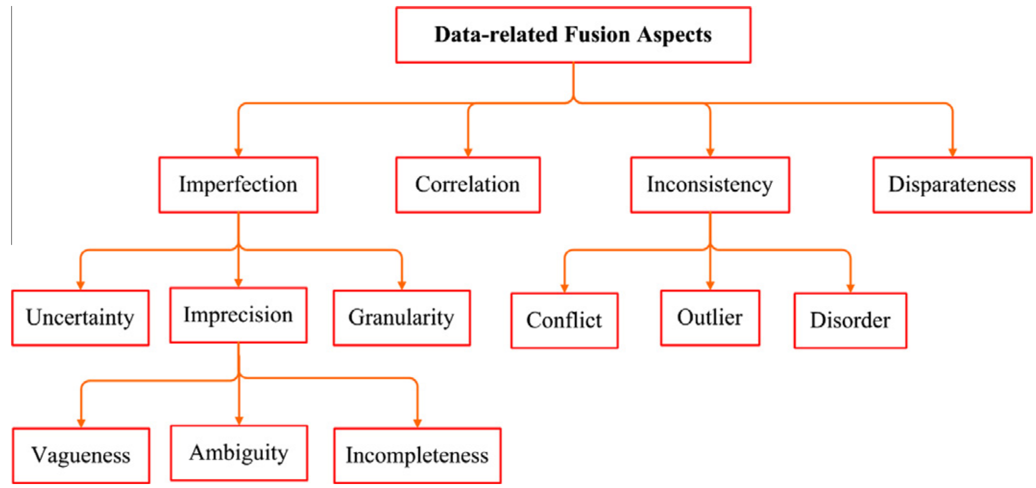


**Fig. 1.** Taxonomy of data fusion methodologies: different data fusion algorithms can be roughly categorized based on one of the four challenging problems of input data that are mainly tackled: namely, data imperfection, data correlation, data inconsistency, and dispírateness of data form.

role in the validity of fusion results. For instance in some recent work [22], the authors performed a probabilistic analysis of the recent history of measurement updates to ensure the freshness of input data, and to improve the efficiency of the data fusion process.

- *Data dimensionality:* the measurement data could be preprocessed, either locally at each of the sensor nodes or globally at the fusion center to be compressed into lower dimensional data, assuming a certain level of compression loss is allowed. This preprocessing stage is beneficial as it enables saving on the communication bandwidth and power required for transmitting data, in the case of local preprocessing [23], or limiting the computational load of the central fusion node, in the case of global preprocessing [24].

While many of these problems have been identified and heavily investigated, no single data fusion algorithm is capable of addressing all the aforementioned challenges. The variety of methods in the literature focus on a subset of these issues to solve, which would be determined based on the application in hand. Our presentation of data fusion literature is organized according to the taxonomy shown in Fig. 1. The existing fusion algorithms are explored based on how various data-related challenges are treated.

## 4. Multisensor data fusion algorithms

Regardless of how different components (modules) of the data fusion system are organized, which is specified by the given fusion architecture, the underlying fusion algorithms must ultimately process (fuse) the input data. As discussed in Section 3, real-world fusion applications have to deal with several data related challenges. As a result, we decided to explore data fusion algorithms according to our novel taxonomy based on data-related aspects of fusion. Fig. 1 illustrates an overview of data-related challenges that are typically tackled by data fusion algorithms. The input data to the fusion system may be imperfect, correlated, inconsistent, and/or in disparate forms/modalities. Each of these four main categories of challenging problems can be further subcategorized into more specific problems, as shown in Fig. 1 and discussed in the following.

Various classifications of imperfect data have been proposed in the literature [25–27]. Our classification of imperfect data is inspired by the pioneering work of Smets' [26] as well as recent elaborations by Dubois and Prade [28]. Three aspects of data imperfection are considereed in our classification: uncertainty, imprecision, and granularity.

Data is uncertain when the associated confidence degree, about what is stated by the data, is less than 1. On the other hand, the imprecise data is that data which refers to several, rather than only one, object(s). Finally, data granularity refers to the ability to distinguish among objects, which are described by data, being dependent on the provided set of attributes. Mathematically speaking, assume the given data $d$ (for each described object of interest) to be structured as the following:

| *object O* | *attribute A* | *statement S* |
|---|---|---|

representing that the data $d$ is stating $S$ regarding the relationship of some attribute(s) $A$ to some object $O$ in the world. Further assume $C(S)$ to represent the degree of confidence we assign to the given statement $S$. Then, data is regarded to be uncertain if $C(S) < 1$ while being precise, i.e., a singleton. Similarly, data is deemed as imprecise if the implied attribute $A$ or degree of confidence $C$ are more than one, e.g. an interval or set. Please note, the statement part of the data are almost always precise.

The imprecise $A$ or $C$ may be well-defined or ill-defined, and/or, miss some information. Thus, imprecision can manifest itself as ambiguity, vagueness, or incompleteness of data. The ambiguous data refers to those data where the $A$ or $C$ are exact and well-defined yet imprecise. For instance, in the sentence "Target position is between 2 and 5" the assigned attribute is the well-defined imprecise interval [25]. The vague data is characterized by having ill-defined attributes, i.e., attribute is more than one and not a well-defined set or interval. For instance, in the sentence "The tower is large" the assigned attribute "large" is not well-defined as it can be interpreted subjectively, i.e., have different meaning from one observer to the other. The imprecise data that has some information missing is called incomplete data. For instance, in the sentence "It is possible to see the chair", only the upper limit on the degree of confidence $C$ is given, i.e., $C < \tau$ for some $\tau$ [29].

Consider an information system [30] where a number of (rather than one) objects $O = \{o_1, \ldots, o_k\}$ are described using a set of attributes $A = \{V_1, V_2, \ldots, V_n\}$ with respective domains $D_1, D_2, \ldots, D_n$. Let $F = D_1 \times D_2 \times \cdots \times D_n$ to represent the set of all possible descriptions given the attributes in $A$, also called the frame. It is possible for several objects to share the same description in terms of these attributes. Let $[o]_F$ to be the set of objects that are equivalently described (thus indistinguishable) within the frame $F$, also called the equivalence class. Now, let $T \subseteq O$ to represent the target set of objects. In general, it is not possible to exactly describe $T$ using $F$, because $T$ may include and exclude objects which are indistinguishable within the frame $F$. However, one can approximate $T$ by the lower and upper limit sets that can be described exactly within $F$ in terms of the induced equivalence classes. Indeed, the Rough set theory discussed in Section 4.1.5. provides a systematic approach to this end. In summary, data granularity refers to the fact that the choice of data frame $F$ (granule) has a significant impact on the resultant data imprecision. In other words, different attribute subset selections $B \subseteq A$ will lead to different frames, and thus different sets of indiscernible (imprecise) objects.

Correlated (dependent) data is also a challenge for data fusion systems and must be treated properly (see Section 4.2). We consider inconsistency in input data to stem from (highly) conflicting, spurious, or out of sequence data. Finally, fusion data may be provided in different forms, i.e. in one or several modalities, as well as generated by physical sensors (hard data) or human operators (soft data).

We believe such categorization of fusion algorithms is beneficial as it enables explicit exploration of popular fusion techniques according to the specific data-related fusion challenge(s) they target. Furthermore, our taxonomy is intended to facilitate ease of development by supplying fusion algorithm designers with an outlook of the appropriate and established techniques to tackle the data-related challenges their given application may involve. Finally, such exposition would be more intuitive and therefore helpful to non-experts in data fusion by providing them with an easy-to-grasp view of the field.

### 4.1. Fusion of imperfect data

The inherent imperfection of data is the most fundamental challenging problem of data fusion systems, and thus the bulk of research work has been focused on tackling this issue. There are a number of mathematical theories available to represent data imperfection [31], such as probability theory [32], fuzzy set theory [33], possibility theory [34], rough set theory [35], and Dempster–Shafer evidence theory (DSET) [36]. Most of these approaches are capable of representing specific aspect(s) of imperfect data. For example, a probabilistic distribution expresses data uncertainty, fuzzy set theory can represent vagueness of data, and evidential belief theory can represent uncertain as well as ambiguous data. Historically, the probability theory was used for a long time to deal with almost all kinds of imperfect information, because it was the only existing theory. Alternative techniques such as fuzzy set theory and evidential reasoning have been proposed to deal with perceived limitations in probabilistic methods, such as complexity, inconsistency, precision of models, and uncertainty about uncertainty [32]. We discuss each of these families of data fusion algorithms, along with their hybridizations that aim for a more comprehensive treatment of data imperfection. Examples of such hybrid frameworks are fuzzy rough set theory (FRST) [37] and fuzzy Dempster–Shafer theory (Fuzzy DSET) [38]. We also describe the new emerging field of fusion using *random sets*, which could be used to develop a unified framework for treatment of data imperfections [39]. Fig. 2 provides an overview of the aforementioned mathematical theories of dealing with data imperfections. On the x-axis, various aspects of data imperfection, introduced in Fig. 1, are depicted. The box around each of the mathematical theories designates the range of imperfection aspects targeted mainly by that theory. The interested reader is referred to [29] for a comprehensive review of the classical theories of representing data imperfections, describing each of them along with their interrelations.

#### 4.1.1. Probabilistic fusion

Probabilistic methods rely on the probability distribution/density functions to express data uncertainty. At the core of these

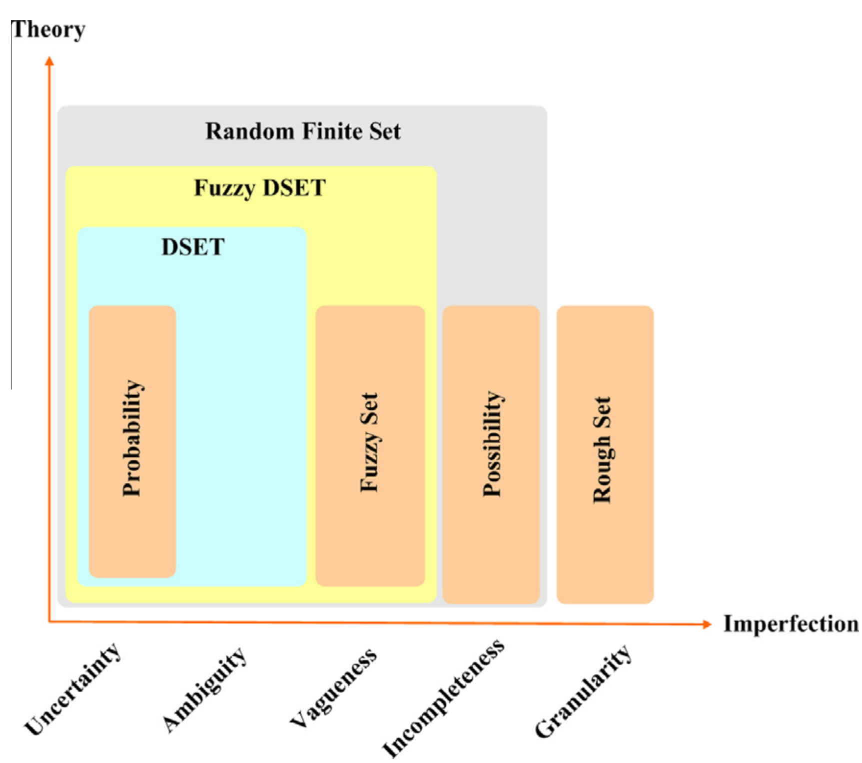


**Fig. 2.** Overview of theoretical frameworks of imperfect data treatment (note: the fuzzy rough set theory is omitted from the diagram to avoid confusion).

methods lies the Bayes estimator, which enables fusion of pieces of data, hence the name "Bayesian fusion". Assuming a state-space representaion, the Bayes estimator provides a method for computing the posterior (conditional) probability distribution/density of the hypothetical state $x_k$ at time $k$ given the set of measurements $Z^k = \{z_1, \ldots, z_k\}$ (up to time $k$) and the prior distribution, as following

$$p(x_k|Z^k) = \frac{p(z_k|x_k)p(x_k|Z^{k-1})}{p(Z^k|Z^{k-1})} \tag{1}$$

where $p(z_k|x_k)$ is called the likelihood function and is based on the given sensor measurement model, $p(x_k|Z^{k-1})$ is called the prior distribution and incorporates the given transition model of the system, and the denominator is a merely a normalizing term to ensure that the probability density function integrates to one.

One can apply the Bayes estimator each time and update the probability distribution/density of the system state by fusing the new piece of data, i.e. $z_k$, recursively. However, both the prior distribution and the normalizing term contain integrals that cannot be evaluated analytically in general. Thus, an analytic solution of the Bayes estimator is occasionally available. Indeed, the well-known Kalman filter (KF) is an exceptional case of the Bayes filter with an exact analytical solution due to enforcing simplifying (and somewhat unrealistic) constraints on the system dynamics to be linear-Gaussian, i.e. the measurement and motion model are assumed to have a linear form and be contaminated with zero-mean Gaussian noise [39]. Nonetheless, the Kalman filter is one of the most popular fusion methods mainly due to its simplicity, ease of implementation, and optimality in a mean-squared error sense. It is a very well established data fusion method whose properties are deeply studied and examined both theoretically and in practical applications. On the other hand, similar to other least-square estimators, the Kalman filter is very sensitive to data corrupted with outliers. Furthermore, the Kalman filter is inappropriate for applications whose error characterics are not readily parameterized.

When dealing with non-linear system dynamics, one usually has to resort to approximation techniques. For instance, the Extended KF [40] and Unscented KF [41], which are extensions of the Kalman filter applicable to non-linear systems, are based on the first-order and second-order approximations as a Taylor series expansion about the current estimate, respectively. However, both of these methods can only handle non-linearities to a limited extent. Grid-based methods [42] provide an alternative approach for approximating non-linear probability density functions, although they rapidly become computationally intractable in high dimensions.

The Monte Carlo simulation-based techniques such as Sequential Monte Carlo (SMC) [43] and Markov Chain Monte Carlo (MCMC) [44] are among the most powerful and popular methods of approximating proabilities. They are also very flexible as they do not make any assumptions regarding the probability densities to be approximated. Particle filters are a recursive implementation of the SMC algorithm [45]. They provide an alternative for Kalman filtering when dealing with non-Gaussian noise and non-linearity in the system. The idea is to deploy a (weighted) ensemble of randomly drawn samples (particles) as an approximation of the probability density of interest. When applied within the Bayesian framework, particle filters are used to approximate the posterior (conditional) probability of the system state as a weighted sum of random samples. The random samples are usually drawn (predicted) from the prior density (transition model) with their weights updated according to the likelihood of the given measurement (sensing model). This approach to the implemenatation of particle filters is referred to as sequential importance sampling (SIS). One usually performs a resampling step where the current set of particles is replaced by a new set drawn from it with probabilities proportional to their weights. This step is included in the original proposal of the particle filters [46], which is called sequential importance resampling (SIR).

Similar to the Kalman filter, the particle filters have been shown to be sensitive to outliers in data, and require a set of auxilary variables to improve their robustness [47]. In addition, when compared to the Kalman filter, particle filters are computationally expensive as they may require a large number of random samples (particles) to estimate the desired posterior probability density. Indeed, they are not suitable for fusion problems involving a high-dimensional state space as the number of particles required to estimate a given density function increases exponentially with dimensionality.

An attractive alternative for particle filters when dealing with high dimensions, are the MCMC algorithms. The underlying idea is to ease the burden of high-dimensional density approximation by using a Markov chain to evolve the samples, instead of simply drawing them randomly (and independently) at each step. Here, a Markov chain is a sequence of random samples generated according to a transition probaility (kernel) function with Markovian property, i.e. the transition probabilities between different sample values in the state space depend only on the random samples' current state. It has been shown that one can always use a well-designed Markov chain that converges to a unique stationary density of interest (in terms of drawn samples) [44]. The convergence occurs after a sufficiently large number of iterations, called the burn-in period. Metropolis and Ulam [48] were the first to deploy this technique for solving problems involving high-dimensional density approximation. Their method was later extended by Hastings [49] and is referred to as the Metropolis–Hastings algorithm. The algorithm works by successively sampling a candidate point from some jumping (proposal) distribution, which is the conditional probability of a potential sample given a current sample. The obtained candidate point is accepted with a probability that is determined based on the ratio of the density at the candidate and current points. The Metropolis–Hastings algorithm is sensitive to the sample initilization and the choice of jumping distribution. Indeed, the burn-in period may be significantly longer for an inappropriate choice of initial samples and/or jumping distribution. Research on the so-called optimal starting point and jumping distribution is the subject of active work. The starting point is typically set as close as possible to the center of distribution, e.g. the distribution's mode. Also, random walks and independent chain sampling are two of the commonly adopted approaches for jumping distribution.

The popular Gibbs sampler is a special case of the Metropolis–Hastings algorithm where the candidate point is always accepted. The keys advanatage of this method is that it considers only univariate conditional distributions, which usually have simpler form and are thus much easier to simulate than complex full joint distributions [50]. Accordingly, the Gibbs sampler simulates $n$ random variables sequentially from the $n$ univariate conditionals rather than generating a single $n$-dimensional vector in a single pass using the full joint distribution. One of the difficulties of applying MCMC methods in practice is to estimate the burn-in time, although it is often suggested that provided a large enough sample size, the burn-in time is not that important. Nonetheless, the effect of burn-in time may not be neglected when parallel processing schemes are deployed to implement MCMC methods [51]. With parallel MCMC the computational load is divided into several pieces, and thus the individual sample sizes may not be as large. To alleviate this problem, the convergence diagnostics methods [52] are commonly used to determine the burn-in time. This has to be done with caution as these methods can potentially introduce some biases of their own into the computations.

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#### 4.1.2. Evidential belief reasoning

The theory of belief functions initiated from Dempster's work [53] in understanding and perfecting Gisher's approach to probability inference, and was then mathematically formalized by Shafer [36] toward a general theory of reasoning based on evidence. Belief functions theory is a popular method to deal with uncertainty and imprecision with a theoretically attractive evidential reasoning framework. Dempster–Shafer theory introduces the notion of assigning beliefs and plausibilities to possible measurement hypotheses along with the required combination rule to fuse them. It can be considered as a generalization to the Bayesian theory that deals with probability mass functions.

Mathematically speaking, consider $X$ to represent all possible states of a system (also called the frame of discernment) and the power set $2^X$ to represent the set of all possible subsets of $X$. In contrast to probability theory that assigns a probability mass to each element of $X$, Dempster–Shafer theory assigns belief mass $m$ to each elemenet $E$ of $2^X$, which represent possible propositions regarding the system state $x$. Function $m$ has two properties as follows:

1. $m(\phi) = 0$
2. $\sum_{E \in 2^X} m(E) = 1$

Intuitively for any proposition $E$, $m(E)$ represents the proportion of available evidence that supports the claim that the actual system state $x$ belongs to $E$. Usually, $m$ is non-zero for only a limited number of sets called the focal elements. Using $m$, a probability interval can be obtained for $E$ as below:

$$bel(E) \leqslant P(E) \leqslant pl(E) \quad (2)$$

where $bel(E)$ is called belief of $E$ and is defined as $bel(E) = \sum_{B \subseteq E} m(B)$ and $pl(E)$ is called plausibility of $E$ and is defined as $pl(E) = \sum_{B \cap E \neq \phi} m(B)$.

Evidence from sensors is usually fused using the Dempster's rule of combination. Consider two sources of information with belief mass functions $m_1$ and $m_2$, respectively. The joint belief mass function $m_{1,2}$ is computed as follows:

$$m_{1,2}(E) = (m_1 \oplus m_2)(E) = \frac{1}{1-K} \sum_{B \cap C = E \neq \phi} m_1(B) m_2(C) \quad (3)$$

$$m_{1,2}(\phi) = 0 \quad (4)$$

where $K$ represents the amount of conflict between the sources and is given by:

$$K = \sum_{B \cap C = \phi} m_1(B) m_2(C) \quad (5)$$

The use of the Dempster–Shafer theory for the data fusion problem was first presented in 1981 by Garvey et al. [54]. Unlike the Bayesian Inference, the Dempster–Shafer theory allows each source to contribute information in different levels of detail. For example, one sensor can provide information to distinguish individual entities, whereas other sensors can provide information to distinguish classes of entities. Furthermore, D–S theory does not assign *a priori* probabilities to unknown propositions; instead probabilities are assigned only when the supporting information is available. In fact, it allows for explicit representation of total ignorance by assigning the entire mass to the frame of discernment, i.e. $m(E = X) = 1$ at any time, whereas using probability theory one has to assume a uniform distribution to deal with this situation. In order to select between the Bayesian and Dempster–Shafer inference one has to maintain a trade-off between the higher level of accuracy offered by the former and the more flexible formulation of the latter [55].

D–S theory has established itself as a promising and popular approach to data fusion especially in the last few years. Nonetheless there are issues such as the exponential complexity of computations (in general worst case scenario) as well as the possibility of producing counterintuitive results when fusing conflicting data using Dempster's rule of combination. Both of these issues have been heavily studied in the literature and numerous strategies have been proposed to resolve or alleviate them. The study by Barrnett [56] was the first to address the computational problems of implementing Dempster's rule of combination. In his proposed algorithm each piece of evidence either confirms or denies a proposition. Gordon and Shortliffe [57] then proposed an improved algorithm that can handle hierarchical evidence. To avoid a very high computational complexity, the algorithm uses approximation to combine evidence, but the approximation cannot not well handle the cases of highly conflicting evidence. Since then several family of complexity reduction approaches based on graphical techniques [58], parallel processing schemes [59], reducing the number of focal elements [60], and coarsening the frame of discernment to approximate the original belief potentials [61] have been studied. Some works have also deployed the finite set representation of focal elements to facilitate fusion computations [62]. Shenoy and Shafer [63] demonstrated the applicability of this local computing method to Bayesian probabilities and fuzzy logics.

As mentioned, the latter issue of fusing conflicting data using Dempster's rule of combination has been an active area of fusion research and has been studied extensively, especially in recent years. Many solutions to this issue have been proposed, which are discussed in detail in Section 4.3.3.

#### 4.1.3. Fusion and fuzzy reasoning

Fuzzy set theory is another theoretical reasoning scheme for dealing with imperfect data. It introduces the novel notion of partial set membership, which enables imprecise (rather than crisp) reasoning [33]. A fuzzy set $F \subseteq X$ is defined by the gradual membership function $\mu_F(x)$ in the interval [0,1] as below:

$$\mu_F(x) \in [0,1] \quad \forall x \in X \quad (6)$$

where the higher the membership degree, the more $x$ belongs to $F$. This makes fuzzy data fusion an efficient solution where vague or partial sensory data is fuzzified using a gradual membership function. Fuzzy data can then be combined using fuzzy rules to produce fuzzy fusion output(s). Fuzzy fusion rules can be divided into conjunctive and disjunctive categories. Examples of the former are the following:

$$\mu_1^{\cap}(x) = min[\mu_{F_1}(x), \mu_{F_2}(x)] \quad \forall x \in X \quad (7)$$

$$\mu_2^{\cap}(x) = \mu_{F_1}(x) \cdot \mu_{F_2}(x) \quad \forall x \in X \quad (8)$$

which represent the standard intersection and product of two fuzzy sets, respectively. Some examples of the latter fuzzy fusion category are

$$\mu_1^{\cup}(x) = max[\mu_{F_1}(x), \mu_{F_2}(x)] \quad \forall x \in X \quad (9)$$

$$\mu_2^{\cup}(x) = \mu_{F_1}(x) + \mu_{F_2}(x) - \mu_{F_1}(x).\mu_{F_2}(x) \quad \forall x \in X \quad (10)$$

which represent the standard union and algebraic sum of two fuzzy sets, respectively. Conjunctive fuzzy fusion rules are considered appropriate when fusing data provided by equally reliable and homogeneous sources. On the other hand, disjunctive rules are deployed when (at least) one of the sources is deemed reliable, though which one is not known, or when fusing highly conflictual data. Accordingly, some adaptive fuzzy fusion rules have been developed, as a compromise between the two categories, that can be applied in both cases. The following fusion rule proposed in [64] is an example for adaptive fuzzy fusion:

$$\mu_{Adaptive}(x) = max\left\{\frac{mu_i^{\cap}(x)}{h(\mu_{F_1}(x), \mu_{F_2}(x))}, min\{1 - h(\mu_{F_1}(x), \mu_{F_2}(x)), \mu_j^{\cup}(x)\}\right\} \quad \forall x \in X \tag{11}$$

where $h(\mu_{F_1}, \mu_{F_2})$ measures the degree of conflict between the graudal membership functions $\mu_{F_1}$ and $\mu_{F_2}$ defined as

$$h(\mu_{F_1}(x), \mu_{F_2}(x)) = max(min\{\mu_{F_1}(x), \mu_{F_2}(x)\}) \quad \forall x \in X \tag{12}$$

and $\mu_i^{\cap}$ and $\mu_j^{\cup}$ are the desired conjunctive and disjunctive fuzzy fusion rules, respectively.

In contrast to the probability and evidence theories, which are well suited to modeling the uncertainty of membership of a target in a well-defined class of objects, fuzzy sets theory is well suited to modeling the fuzzy membership of a target in an ill-defined class. Yet, similar to probability theory that requires prior knowledge of probability distributions, fuzzy sets theory requires prior membership functions for different fuzzy sets. Due to being a powerful theory to represent vague data, fuzzy set theory is particularly useful to represent and fuse vague data produced by human experts in a linguistic fashion. Furthermore, it has been often integrated with probabilistic [160,66] and D–S evidential [38,67] fusion algorithms in a complementary manner.

#### 4.1.4. Possibilistic fusion

Possibility theory was founded by Zadeh [34] and later extended by Dubois and Prade [68,69]. It is based on fuzzy set theory, but was mainly designed to represent incomplete rather than vague data. Indeed possibility theory's treatment of imperfect data is similar in spirit to probability and D–S evidence theory with a different quantification approach [29]. The model of imperfect data in possibility theory is the possibility distribution $\pi_B(x) \in [0,1]$ $\forall x \in X$, which characterizes the uncertain membership of an element $x$ in a (well-defined) known class $B$. This is distinguished from the gradual membership function $\mu_F(x)$ of fuzzy set theory, which characterizes the membership of $x$ in an ill-defined fuzzy set $F$. Another important distinction is the normalization constraint that requires that at least one value is totally possible, i.e. $\exists x^* \in X$ *s.t.* $\pi_B(x^*) = 1$. Given the possibility distribution $\pi_B(x)$, the possibility measure $\Pi(U)$ and necessity measure $N(U)$ of an event $U$ are defined as below

$$\Pi(U) = max_{x \in U}\{\pi_B(x)\} \quad \forall U \subseteq X \tag{13}$$

$$N(U) = min_{x \notin U}\{1 - \pi_B(x)\} \quad \forall U \subseteq X \tag{14}$$

A possibility degree $\Pi(U)$ quantifies to what extent the event $U$ is plausible, while the necessity degree $N(U)$ quantifies the certainty of $U$, in the face of incomplete information expressed by $\pi(x)$ [70]. The possibility and necessirty measures can also be interpreted as a special case of upper and lower probabilities, in connection with the probability theory [71].

The data combination rules used for possibilistic fusion are similar to those deployed for fuzzy fusion. The main difference is that possibilistic rules are always normalized. The choice of appropriate fusion rules is dependent on the how agreeable the data sources are, and also what is known about their reliability [69]. However, the basic symmetric conjunctive and disjunctive fusion rules of fuzzy set theory are sufficient only for restricted cases. There are a number of enhancements of possibilistic fusion methods that allow for handlinig more difficult fusion scenarios. For instance, assuming $0 \leqslant \lambda_i \leqslant 1$ to represent the perceived reliability of the $i$th source for a set of unequally reliable sources, one can modify the associated possibility distribution $\pi_i$ of the source using the discounting approach as $\pi_i' = max(\pi_i, 1 - \lambda)$ to incorporate its reliability into the fusion process [68].

Although possibility theory has not been commonly used in the data fusion community, some researchers have studied its performance in comparison to probabilistic and evidential fusion approaches [72], where it was shown to be capable of producing competitive results. Also, possibilistic fusion is argued to be most appropriate in poorly informed environments (no statistical data available) as well as in fusion of heterogeneous data sources [64]. For example, a recent work by Benferhat and Sossai [73] has demonstrated the effectiveness of possibilistic fusion for robot localization in partially known indoor environments.

#### 4.1.5. Rough set based fusion

Rough set is a theory of imperfect data developed by Pawlak [35] to represent imprecise data, ignoring uncertainty at different granularity levels. Indeed, the Rough set theory enables dealing with data granularity. It provides means of approximating a crisp target set $T$ within a given frame $F_B$ designated by the set $B \subseteq A$, which is the specific set of attributes chosen to describe objects. The approximation is represented as a tuple $\langle B_*(T), B^*(T)\rangle$, where $B_*(T)$ and $B^*(T)$ represent the lower and upper approximations of set $T$ within frame $F_B$, repectively, and are defined as below [74]

$$B_*(T) = \{o | [o]_{F_B} \subseteq T\} \tag{15}$$

$$B^*(T) = \{o | [o]_{F_B} \cap T \neq \phi\} \tag{16}$$

and $B_*(T) \subseteq T \subseteq B^*(T)$. The lower approximation $B_*(T)$ can be interpreted as a conservative approximation that includes only objects that are definitely a member of $T$, whereas the upper approximation $B^*(T)$ is more liberal in including all objects that can possibly belong to $T$. Based on this approximation, the boundary region of $T$ is defined as $BN_B(T) = B^*(T) - B_*(T)$ which is the set of objects that can neither be classified as belonging nor not-belonging to $T$. Accordingly, a set $T$ is considered rough if $BN_B(T) \neq \phi$.

Within the data fusion framework, $T$ can be considered as representing the imprecise set of (target) states of a system (instead of abstract objects). Then, Rough set theory would allow the approximation of possible states of the system based on the granularity of input data, i.e. $F_B$. Once approximated as rough sets, data pieces can be fused using classic set theory conjunctive or disjunctive fusion operators, i.e. intersection or union, respectively.

In order to perform fusion successfully, data granules must be neither too fine nor too rough. In the case of data granules being too fine, i.e. $[o]_{F_B}$ being singletons, the Rough set theory reduces to classical set theory. On the other hand, for very rough data granules, i.e. $[o]_{F_B}$ being very large subsets, the lower approximation of data is likely to be empty, resulting in total ignorance. The major advantage of Rough set compared to other alternatives is that it does not require any preliminary or additional information such as data distribution or membership function [75]. Rough set theory allows for fusion of imprecise data approximated based merely on its internal structure (granularity).

Due to being a relatively new theory and not well understood within fusion community, Rough set theory has been rarely applied to data fusion problems. Some work has been reported on data fusion systems using Rough set theory [76,77], where it provides a means to select the most informative set of attributes (sensors) regarding the goal of the fusion system, e.g. classification of objects. The idea is to use a rough integral as the measure of relevance for each sensor, and filter out sensors below the given threshold.

#### 4.1.6. Hybrid fusion approaches

The main idea behind development of hybrid fusion algorithms is that different fusion methods such as fuzzy reasoning, D–S evidence theory, and probabilistic fusion should be not be competing, as they approach data fusion from different (possibly complementary) perspectives. At the theoretical level, hybridization of fuzzy set theory with D–S evidence theory has been studied frequently

[78,38] aiming at providing a framework for more comprehensive treatment of data imperfection. Among many such proposals, the work by Yen [38] is perhaps the most popular approach that extends D–S evidence theory into the fuzzy realm while maintaining its major theoretical principles. Yen's theory of fuzzy D–S evidence theory has been frequently used in the literature. For instance, Zue and Basir [67,79] developed a hybrid fusion system applied to an image segmentation problem, which is based on a fuzzy Dempster–Shafer evidential reasoning scheme.

Combination of fuzzy set theory with Rough set theory (FRST), proposed by Dubois and Prade, is another important theoretical hybridization existing in the literature [37]. In spite of being a powerful representation tool for vague as well as ambiguous data, the original FRST has some limitations such as relying on special fuzzy relations. This issue has been recently addressed by Yeung et al. [80] in an attempt to generalize FRST to arbitrary fuzzy relations. Application of FRST to data fusion has not often been investigated in the fusion literature as Rough set theory itself is still not an established data fusion approach. Nonetheless, some preliminary work has been reported [81].

#### *4.1.7. Random set theoretic fusion*

The principles of random sets theory were first proposed to study integral geometry in 1970s [82]. The unifying capability of random set theory has been shown by several researchers [83,84,16], among them, the work of Goodman et al. [16] has been most successful in gaining attention. The most notable work on promoting random set theory as a unified fusion framework has been done by Mahler in his papers [20,16,85] and recent book [39]. In particular, in his book he attempts to present a detailed exposition of random set theory and its application to general single-target as well as multi-target data fusion problems.

Random set theory is usually deemed as an ideal framework for extending the popular Bayes filter (see Section 4.1.1) from single-target (modeled by a random variable) into multi-target (modeled by a random set). Accordingly, the majority of research work has been focused on applying random set theory to tracking of multiple targets. This generalization is not a straightforward procedure and is only possible provided that an appropriate calculus of random finite sets is formulated [20]. Indeed, within random set theory data, i.e. target states and measurements, are modeled as random sets of finite size instead of conventional vectors. Having done this, priors and likelihood functions are constructed that are capable of modeling a wide range of different phenomena. For instance, phenomena related to the system dynamics such as target disappearance/appearance, extended/unresolved targets, and target spawning, as well as measurement-related phenomena such as missed detection and false alarms can be explicitly represented.

Obviously, one cannot expect to solve for this multi-target tracking analytically (as was not the case for single-target Bayes filter). Therefore, different approximation techniques are devised to compute the Bayes update equation. The moment matching techniques have been very successful in approximating the single-target Bayes filter. For instance, Kalman filter relies on propagating the first two moments (i.e. mean and covariance) while alpha–beta filters match only the first moment. In case of multi-target tracking, the first moment is the Probability Hypothesis Density (PHD), which is used to develop a filter with the same title, i.e. PHD filter [86]. There is also a higher order extension of this filter called Cardinalized Probability Hypothesis Density (CPHD) filter [87,88], which propagates the PHD as well as the full probability distribution of the random variable representing the number of targets. Both PHD and CPHD filters involve integrals that prevent direct implementation of a closed form solution. As a result two approximation methods, namely, Gaussian Mixture (GM) and Sequential Monte Carlo (SMC), have been used in the literature to further ease the implementation stage for these filters [89,90]. Both of these methods have been evaluated and shown to compare favorably with alternative approaches such as JPDA [88] and MHT [91], while being less computationally demanding than either. One important advantage of the (C)PHD family of filters is to avoid the data association problem, but this also means that maintaining track continuity can become a challenging task. For a review of recent work on the (C) PHD filter, the interested reader is referred to [92].

Random set theory has also been recently shown to be able to efficiently solve fusion related tasks such as target detection [93], tracking [94], identification [29], sensor management [95], and soft/hard data fusion [96]. Nonetheless, further research through more complex test scenarios in diverse applications should be performed to prove its performance as a unifying framework for fusion of imperfect data. Table 1 presents a comparative overview of the imperfect data fusion frameworks discussed in this section.

**Table 1**
Comparison of imperfect data fusion frameworks.

| Framework | Characteristics | Capabilities | Limitations |
|---|---|---|---|
| Probabilistic [32,40,45] | Represents sensory data using probability distributions fused together within Bayesian framework | Well-established and understood approach to treat data uncertainty | Considered incapable of addressing other data imperfection aspects |
| Evidential [36,54–56,58] | Relies on probability mass to further characterize data using belief and plausibilities and fuses using Dempsters' combination rule | Enables fusion of uncertain and ambiguous data | Does not deal with other aspects of data imprecision, inefficient for fusion of highly conflicting data |
| Fuzzy reasoning [160,66,67] | Allows vague data representation, using fuzzy memberships, and fusion based on fuzzy rules | Intuitive approach to deal with vague data esp. human generated | Limited merely to fusion of vague data |
| Possibilistic [29,72,64] | Similar in data representation to probabilistic and evidential frameworks and fusion to fuzzy framework | Allows for handling incomplete data common in poorly informed environment | Not commonly used and well understood in fusion community |
| Rough set theoretic [35,97,75,77] | Deals with ambiguous data using precise approximate lower and upper bounds manipulated using classical set theory operators | Does not require any preliminary or additional information | Requires appropriate level of data granularity |
| Hybridization [78,38,67,79] | Aims at providing a more comprehensive treatment of imperfect data | Deploys fusion framework in a complementary rather than competitive fashion | Rather ad hoc generalization of one fusion framework to subsume other(s), extra computational burden |
| Random set theoretic [20,16,85,39] | Relies on random subsets of measurement/state space to represent many aspects of imperfect data | Can potentially provide a unifying framework for fusion of imperfect data | Relatively new and not very well appreciated in fusion community |

### 4.2. Fusion of correlated data

Many data fusion algorithms, including the popular KF approach, require either independence or prior knowledge of the cross covariance of data to produce consistent results. Unfortunately, in many applications fusion data is correlated with potentially unknown cross covariance. This can occur due to common noise acting on the observed phenomena [98] in centralized fusion settings, or the rumor propagation issue, also known as data incest or double counting problem [99], where measurements are inadvertently used several times in distributed fusion settings [3]. If not addressed properly, data correlation can lead to biased estimation, e.g. artificially high confidence value, or even divergence of fusion algorithm [100]. For KF-based systems, the optimal KF approach exists that allows for maintaining cross covariance information between updates [3]. However, it is not typically desirable, as it is shown to scale quadratically with the number of updates [101]. Also, in case of data incest, an exact solution is to keep track of pedigree information which includes all sensor measurements that have contributed to a certain estimate [102]. This solution is not appealing as it does not scale well with the number of fusion nodes [103]. Most of the proposed solutions to correlated data fusion attempt to solve it by either eliminating the cause of correlation or tackling the impact of correlation in fusion process.

#### 4.2.1. Eliminating data correlation

Data correlation is especially problematic in distributed fusion systems and is commonly caused by data incest. The data incest situation itself happens when the same information takes several different paths from the source sensor to the fusion node or due to cyclic paths through which the information recirculates from output of a fusion node back to the input [104,3]. This issue can be eliminated (before fusion) either explicitly by removal of data incest [105] or implicitly through reconstruction of measurements [106]. The former family of approaches usually assume a specific network topology as well as fixed communication delays, although recent extensions consider the more general problem of arbitrary topologies with variable delays using graph theoretic algorithms [107,108]. The latter approaches attempt to form a decorrelated sequence of measurements by reconstructing them such that the correlation with previous intermediate updates from current intermediate state updates is removed. The decorrelated sequence is then fed to the global fusion processor as input to a filtering algorithm. Extensions in this family consider more complex fusion scenarios with existence of clutter, data association, and interacting targets [109].

#### 4.2.2. Data fusion in presence of unknown correlations

Instead of removing data correlation, one can design a fusion algorithm that accounts for correlated data. Covariance Intersection (CI) [98] is the most common fusion method to deal with correlated data. CI was originally developed to avoid the problem of covariance matrix underestimation due to data incest. It solves this problem in general form for two data sources (i.e. random variables) by formulating an estimate of the covariance matrix as a convex combination of the means and covariances of the input data. CI has been shown to be optimal, in terms of finding the upper bound for the combined covariances [110], as well as theoretically sound and applicable to any probability distribution function, from information theory perspective [111].

On the other hand, CI requires a non-linear optimization process and is therefore computationally demanding. Furthermore, it tends to overestimate the intersection region, which results in pessimistic results and consequent degradation of fusion performance. Some faster variants of CI have been proposed attempting to alleviate the former issue [112,113]. The Largest Ellipsoid (LE) algorithm was developed, as an alternative to CI, to address the latter issue [114]. LE provides a tighter estimate of covariance matrix by finding the largest ellipse that fits within the intersection region of the input covariances. It has been recently argued that LE's formula derivation for the center of Largest Ellipsoid is not appropriate and a new algorithm, called Internal Ellipsoid Approximation (IEA), is proposed to accomplish this task [115]. One major limitation with all these methods is their inability to facilitate fusion of correlated data within a more powerful fusion framework than KF-based techniques, such as particle filters [3]. Very recently, a fusion framework based on an approximation to the generalized CI algorithm, called Chernoff fusion method, is proposed, which tackles the generic problem of fusing any number of correlated PDFs [116]. An overview of the discussed correlated data fusion methodologies is presented in Table 2.

### 4.3. Fusion of inconsistent data

The notion of data inconsistency, as applied in this paper, is in a generic sense and encompasses spurious, as well as disordered and conflicting data. We explore various techniques in the data fusion literature which are developed to tackle each of the three aspects of data inconsistency.

#### 4.3.1. Spurious data

Data provided by sensors to the fusion system may be spurious due to unexpected situations such as permanent failures, short duration spike faults, or slowly developing failure [18]. If fused with correct data, such spurious data can lead to dangerously inaccurate estimates. For instance, KF would easily break down if exposed to outliers [117]. The majority of work on treating spurious data has been focused on identification/prediction and subsequent elimination of outliers from the fusion process. Indeed, the literature work on sensor validation is partially aiming at the same target [118–120]. The problem with most of these techniques is the requirement for prior information, often in the form of specific failure model(s). As a result, they would perform poorly in a general case where prior information is not available or unmodeled failures occur [121]. Recently, a general framework for detection of spurious data has been proposed that relies on stochastic adaptive modeling of sensors and is thus not specific to any prior sensor

**Table 2**
Summary of correlated data fusion methods.

| Framework | Algorithms | Characteristics |
|---|---|---|
| Correlation elimination | Explicit removal [105,107,108] | Usually assumes a specific network topology and fixed communication delays |
| | Measurement reconstruction [106,109] | Applicable to more complex fusion scenarios |
| Correlation presence | Covariance Intersection [98,110] | Avoids the covariance underestimation problem, yet computationally demanding and rather pessimistic |
| | Fast CI [112,113] | Enhanced efficiency through alternative non-linear optimization processes |
| | Largest Ellipsoid [114] | Provides a tighter (less pessimistic) covariance estimate, yet limited to KF-based fusion like the others |

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failure model [18,122]. It is developed within the Bayesian fusion framework by adding a term to the common formulation that represents the probabilistic estimate that the data is not spurious conditioned upon the data and the true state. The intended effect for this term is increasing the variance of the posterior distribution when data from one of the sensors is inconsistent with respect to the other. Extensive experimental simulations have shown the promising performance of this technique in dealing with spurious data [121].

#### 4.3.2. Out of sequence data

The input data to the fusion system is usually organized as discrete pieces each labeled with a timestamp designating its time of origin. Several factors such as variable propagation times for different data sources as well as having heterogeneous sensors operating at multiple rates can lead to data arriving out of sequence at the fusion system. Such out of sequence measurements (OOSM) can appear as inconsistent data to the fusion algorithm. The main issue is how to use this, usually old, data to update the current estimate while taking care of the correlated process noise between the current time and the time of the delayed measurement [123]. A trivial solution to OOSM is to simply discard it. Such solution would cause information loss and severe fusion performance degradation if OOSM is prevalent in the input data. Another intuitive solution is to store all input data in order and reprocess it once OOSM is received. This approach yields optimal performance yet is impractical due to having intense computational and storage requirements. There has been considerable amount of research done in this area in the last decade due to the increasing popularity of distributed sensing and tracking systems [123]. We explore these methods according to their assumed number of step lags as well as number of tracking targets.

Most of the early work on OOSM assumed only single-lag data. For example, an approximate sub-optimal solution to OOSM called "Algorithm B" [124] as well as its famous optimal counterpart "Algorithm A" [125], both assume single-lag data. Some researchers have proposed algorithms to enable handling of OOSM with arbitrary lags [126–128]. Among these methods the work in [128] is particularly interesting as it provides a unifying framework for treating OOSM with "Algorithm A" as special case. Nonetheless, it was shown in [129] that this approach along with many other multi-lag OOSM methods are usually very expensive in terms of computational complexity and storage. The same authors proposed an extension to the "Algorithm A" and "Algorithm B" called "algorithm A*l*1" and "Algorithm B*l*1", respectively. They further showed that these new algorithms have requirements similar to their single-lag counterparts and are therefore recommended for practical applications, especially "Algorithm B*l*1" is preferred due to being almost optimal and very efficient. Some recent work also investigates the OOSM problem in case of having both single-lag and multiple-lag data, termed the mixed-lag OOSM problem. The proposed algorithm is claimed to handle all three types of OOSM data and is shown to be suboptimal in the linear MMSE sense under one approximation [130].

The bulk of research on the OOSM problem has been traditionally concentrated on an OOSM filtering algorithm that considers only a single-target, and does not address issues pertinent to data association and the presence of clutter that arise in multi-target fusion scenarios [131]. This problem has received attention in recent years and several methods tackling various aspects of OOSM in multi-target tracking have been proposed. In [131], a multitarget OOSM dwell-based tracking algorithms is proposed which includes gating, likelihood computation, and hypothesis management; and the single-lag and two-lag OOSM problems are discussed. In [132], the authors present a generic framework that enables straightforward extension of many single-target OOSM solutions to efficient algorithms in the multi-target data association case. The problem of out of sequence data for disordered tracks, instead of measurements, termed OOST, is explored in [133]. The OOST problem is solved using equivalent measurements obtained from individual sensor tracks, which are then used in an augmented state framework to compute the joint density of the current target state and the target state corresponding to the delayed data. Generally, in comparison with the OOSM problem, the OOST problem is much less studied in the literature. More recently, the three popular algorithms for the OOSM problem proposed by Bar-Shalom [134] are adapted to handle the OOST problem. This work is expected to improve the research community's understanding of the OOST problem.

#### 4.3.3. Conflicting data

Fusion of conflicting data, when for instance several experts have very different ideas about the same phenomenon, has long been identified as a challenging task in the data fusion community. In particular, this issue has been heavily studied for fusion within the Dempster–Shafer evidence theory framework. As shown in a famous counterexample by Zadeh [135], naive application of Dempster's rule of combination to fusion of highly conflicting data results in unintuitive results. Since then Dempster's rule of combination has been subject to much criticism for rather counter-intuitive behavior [136]. Most of the solutions proposed alternatives to Dempster's rule of combinations [137–140]. On the other hand, some authors have defended this rule, arguing that the counter-intuitive results are due to improper application of this rule [141,142,39]. For example, in [39] Mahler shows that the supposed unintuitive result of Dempster's combination rule can be resolved using a simple corrective strategy, i.e. to assign arbitrary small but non-zero belief masses to hypotheses deemed extremely unlikely. Indeed, proper application of Dempsters rule of combination requires satisfaction of the following three constraints: (1) independent sources providing independent evidences, (2) homogeneous sources defined on a unique frame of discernment, and (3) a frame of discernment containing an *exclusive* and *exhaustive* list of hypotheses.

These constraints are too restrictive and difficult to satisfy in many practical applications. As a result DSET has been extended to more flexible theories such as Transferable Belief Model (TBM) [138] and DezertSmarandache theory (DSmT) [139]. The former theory extends DSET by refuting the *exhaustivity* constraint, i.e. open-world assumption, and allowing elements outside the frame of discernment to be represented by the empty set. The latter refutes the *exclusivity* constraint allowing compound elements, i.e. elements of the hyper power set, to be represented. The theoretical justification for TBM was recently presented by Smets [19]. In this work, he provides an exhaustive review of the existing combination rules in an attempt to shed light on their applicability as well as theoretical soundness. He argues that the majority of proposed combination rules are ad hoc in nature and lack appropriate theoretical justification. It is also demonstrated that most of the alternative combination rules are indeed conjunctive fusion operators that redistribute the global (or partial) conflicting belief mass among some elements of the power set. This relies on the notion that if experts agree on some evidence, they are considered reliable, and otherwise at least one of them is unreliable and the disjunctive fusion rules are deployed. But disjunctive rules usually result in degradation in data specificity. Therefore, the reliability of the expert sources must be either known *a priori* or estimated [143].

Fusion of conflicting data within the Bayesian probabilistic framework has also been explored by some authors. For example, Covariance Union (CU) algorithm is developed to complement the CI method, and enable data fusion where input data is not just

**Table 3**
Overview of inconsistent data fusion methodologies.

| Inconsistency aspect | Problem | Resolution strategy | Characteristics |
|---|---|---|---|
| Outlier | If fused with correct data, can lead to dangerously inaccurate estimates | Sensor validation techniques [118–120] | Identification/predication and subsequent removal of outliers, typically restricted to specific prior-known failure models |
| | | Stochastic adaptive sensor modeling [121] | General framework for detection of spurious data without prior knowledge |
| Disorder | Update current estimate using old measurements (OOSM) | Ignore, reprocess, or use backward/ forward prediction [124,125,123,128,146] | Mostly assume single-lag delays and linear target dynamics |
| | Update current estimate using old track estimates (OOST) | Use augmented state framework to incorporate delayed estimates [133,134] | Much less understood and studied in the literature |
| Conflict | Non-intuitive results while fusing highly conflicting data using Dempsters' combination rule | Numerous alternative combination rules [137–140] | Mostly ad hoc in nature without proper theoretical justification |
| | | Apply corrective strategies while using Dempsters' rule [141,142,39] | Defend validity of Dempsters' rule provided that certain constraints are satisfied |

correlated but may also be conflicting [144]. Furthermore, a new Bayesian framework for fusion of uncertain, imprecise, as well as conflicting data was proposed recently [145]. Authors exploit advances in the Bayesian research arena to develop Bayesian models with similar theoretical properties as TBM and DSmT theories allowing for consistent probabilistic fusion of conflicting data. Table 3 provides a summary of the discussed literature work on inconsistent data fusion.

### 4.4. Fusion of disparate data

The input data to a fusion system may be generated by a wide variety of sensors, humans, or even archived sensory data. Fusion of such disparate data in order to build a coherent and accurate global view or the observed phenomena is a very difficult task. Nonetheless, in some fusion applications such as human computer interaction (HCI), such diversity of sensors is necessary to enable natural interaction with humans. Our focus of discussion is on fusion of human generated data (soft data) as well as fusion of soft and hard data, as research in this direction has attracted attention in recent years. This is motivated by the inherent limitations of electronic (hard) sensors and recent availability of communication infrastructure that allow humans to act as soft sensors [147]. Furthermore, while a tremendous amount of research has been done on data fusion using conventional sensors, very limited work has studied fusion of data produced by human and non-human sensors. An example of preliminary research in this area includes the work on generating a dataset for hard/soft data fusion intended to serve as a foundation and a verification/validation resource for future research [148,149]. Also in [147], the authors provide a brief review on ongoing work on dynamic fusion of soft/hard data, identifying its motivation and advantages, challenges, and requirements. Very recently, a Dempster–Shafer theoretic framework for soft/hard data fusion is presented that relies on a novel conditional approach to updating as well as a new model to convert propositional logic statements from text into forms usable by Dempster–Shafer theory [150]. Furthermore, some new work investigates the problem of uncertainty representation for linguistic data [151]. The authors describe various types of uncertainty inherent in the nature of human languages as well as some tools to perform linguistic disambiguation such as lexicons, grammars, and dictionaries.

Another new direction of work is focused on the so called *human centered data fusion* paradigm that puts emphasis on the human role in the fusion process [152]. This new paradigm allows human to participate in the data fusion process not merely as soft sensors, but also as hybrid computers and ad hoc teams (hive mind). It relies on emerging technologies such as virtual worlds and social network software to support humans in their new fusion roles. In spite of all these developments, research on hard/soft data fusion as well as human centered fusion is still in the fledging stage, and believed to provide rich opportunities for further theoretical advancement and practical demonstrations in the future.

## 5. Discussion and remarks

Our discussion in this section is an attempt to shed light on some of the emerging trends and frameworks in the sensor data fusion field. In addition, we explore many of the fusion aspects that are the subject of active ongoing research. In contrast to emerging paradigms, research in these aspects is more established, although still rather poorly understood or developed.

### 5.1. Emerging fusion paradigms

#### 5.1.1. Soft/hard data fusion

In comparison to conventional fusion systems where input data is generated by calibrated electronic sensor systems with well-defined characteristics, research on soft data fusion considers combining human-based data expressed preferably in unconstrained natural language. Soft data fusion is a complex problem, which has not been the focus of research in the fusion community [153]. The fusion of soft and hard data is even more challenging yet necessary in some applications [147]. Recent developments in the literature such as the *human centered* data fusion paradigm [152] as well as preliminary work on soft/hard fusion [150,149,154] are an indicator of the new trend towards a more general data fusion framework where both human and non-human sensory data can be processed efficiently.

#### 5.1.2. Opportunistic data fusion

Regarding the limitations of traditional data fusion systems, which are mostly designed to use dedicated sensor and information resources, and the availability of new ubiquitous computing and communication technologies, the opportunistic data fusion paradigm considers the possibility of treating sensors as shared resources and performing fusion in an opportunistic manner [155]. New challenging problems associated with such fusion systems

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are identified and novel approaches to tackle them are explored. Some of the distinctions of the opportunistic information fusion model (OIFM) compared to the conventional approach are the need for on-the-fly discovery of sensors, ad hoc computational load, and dynamic (not pre-defined) fusion rules. The key enabling component required to realize an OIFM is a new approach towards middleware development called opportunistic middleware model (OMM). This is because, the existing middleware platforms do not scale to the device diversity, size, and runtime dynamics required by OIFM applications [155]. Unfortunately, current specifications for the OMM does not address many issues related to its implementation and thus future reserach is still needed to make OIFM viable. Nonetheless, some preliminary reserach work is reported in the literature. For instance, in [156] an opportunistic fusion of data across time, space, and feature level is performed in a visual sensor network to achieve human gesture analysis. In [157], the authors study the problem of optimal camera placement in a visual sensor network designed to serve multiple applications (each to be operated in an opportunistic manner). The problem is formulated as an multi-objective optimization problem and solved efficiently using a multi-objective genetic algorithm.

#### 5.1.3. Adaptive fusion and learning

Adaptation enables data fusion in situations where required environment parameters are not known *a prior* or change dynamically and thus must be re-estimated on-the-fly. Early work on adaptive data fusion dates back to the early 1990s [158]. Nonetheless, this problem has been rarely explored in the fusion literature until recently. Some of the existing work is focused on incorporation of adaptivity into the Kalman filtering algorithm. In [159] an adaptive fusion system capable of intelligent allocation of limited resources is described that enables efficient tracking of moving targets in 3D. An adaptive variant of KF called FL-AKF is proposed in [65] that relies on fuzzy inference based on covariance matching to adaptively estimate the covariance matrix of measurement noise. In a similar approach, in [161] the authors present a novel adaptive Kalman filter (NAKF) that achieves adaptation using a mathematical function termed degree of matching (DoM), which is based on covariance matching. Very recently, an adaptive UKF algorithm with multiple fading factors-based gain correction is proposed and applied to the pico satellite attitude estimation problem [162]. Another trend of work investigates explicit integration of machine learning algorithms into the fusion process to accomplish adaptation. For example, machine learning methods are deployed in [163] to achieve on-line adaptation to users' multimodal temporal thresholds within a human computer interaction application framework. Some other work studies application of reinforcement learning to adaptive fusion systems to perform dynamic data reliability estimation [164,165]. A recent work also proposed using kernel-based learning methods to achieve adaptive decision fusion rules [166].

### 5.2. Ongoing data fusion research

#### 5.2.1. Automated fusion

Research in this area is based on a formalization of data fusion within formal logic and category theory frameworks. The main objective is to develop a formal theory of fusion that would allow researchers to specify various fusion concepts and requirements in a unique (standard) way [17]. The advantages of such theory are twofold: (1) Characteristics related to a newly proposed fusion method would be formally provable. (2) Developers could specify their design in a formal language and then use the formal methods approach to synthesize and evaluate the desired fusion system. The latter advantage is particularly useful as it enables rapid and machine-automated prototyping of data fusion algorithms. Nonetheless, the notion of automated development of fusion algorithms based on this formalism is still a distant goal that requires further investigation – although its feasibility has been shown through an example of high-level data fusion algorithm synthesis based on given specification [167].

#### 5.2.2. Belief reliability

The majority of data fusion literature work is based on an optimistic assumption about the reliability of underlying models producing the beliefs associated with imperfect data. For instance, sensory data is commonly considered as equally reliable and play a symmetrical role in the fusion process [7]. Nonetheless, different models usually have different reliabilities and are only valid for a specific range. A recent trend in data fusion has addressed this issue mostly by attempting to account for reliability of beliefs. This has been accomplished through introduction of the notion of a second level of uncertainty, i.e. uncertainty about uncertainty, represented as reliability coefficients. The main challenges are first to estimate these coefficients, and then to incorporate them into the fusion process. A number of approaches to estimate reliability coefficients have been proposed which rely on domain knowledge and contextual information [168], learning through training [169], possibility theory [170], and expert judgments [171]. Furthermore, the problem of reliability incorporation has been studied within several fusion frameworks such as Dempster–Shafer theory [172], fuzzy and possibility theory [69], Transferable Belief Model [173], and probability theory [174]. More recent work also investigates the impact of belief reliability on high-level data fusion [175]. The issue of reliability in data fusion is still not well established, and several open questions such as interrelationship between reliabilities, reliability of heterogeneous data, and a comprehensive architecture to manage data fusion algorithm and reliability of data sources remains as a part of future research [7,172].

#### 5.2.3. Secure fusion

Data integrity, confidentiality, and freshness are security issues that are required in many data fusion applications, particularity in the military. There are some protocols for secure data fusion recently proposed in the literature. In [176], a secure fusion framework called Blind Information Fusion Framework (BIFF) is proposed, which enables confidentiality-preserving data fusion. A procedure is described to transform data from normal space to the anonymous space where, once fused, data cannot be deduced. Also, in [177] an algorithm called Random Offset Method (ROM) is presented to ensure mutual privacy in distributed fusion systems based on a consensus averaging method. ROM achieves its goal by first obfuscating fusion data through a noisification process, thus hiding it from other fusion parties, and then exploiting the high-frequency elimination property of consensus filter to recover noisified data at the fusion stage.

In spite of these preliminary efforts, the security aspect of data fusion systems is still largely unexplored especially in large scale sensor networks with vast coverage area where it is even more critical. Therefore, integrating security as an essential component of data fusion systems is an interesting issue for future research. Indeed, it is already being actively researched for the related problem of data aggregation within sensor network community [178,179], which further signifies the importance of considering security-related issues while developing modern decentralized fusion systems.

#### 5.2.4. Fusion evaluation

Performance evaluation aims at studying the behavior of a data fusion system operated by various algorithms and comparing their pros and cons based on a set of measures or metrics. The outcome is typically a mapping of different algorithms into different real values or partial orders for ranking [180]. Generally speaking, the obtained performance of a data fusion system is deemed to be dependent on two components, namely, the quality of input data, and the efficiency of fusion algorithm. As a result, the literarture work on (low level) fusion evaluation can be categorized into the following groups:

- *Evaluating the quality of input data to the fusion system:* the target here is to develop approaches that enable quality assessment of the data, which are fed to the fusion system, and calculation of the degree of confidence in data in terms of attributes such as reliability and credibility [181]. The most notable work in this group are perhaps the standardization agreements (STANAG) 2022 [182] of NATO.[1] STANAG adopts an alphanumeric system of rating, which combines a measurement of the reliability of the source of information with a measurement of the credibility of that information, both evaluated using the existing knowledge. STANAG recommendations are expressed using natural language statements, which makes them quite imprecise and ambiguous. Some researchers attempted to analyze these recommendations and provide a formal methematical system of information evaluation in compliance with the NATO recommendations [183,181]. The proposed formalism relies on the observation that three notions underline an information evaluation system: the number of independent sources supporting an information, their reliability, and that the information may conflict with some available/prior information. Accordingly, a model of evaluation is defined and an its fusion method, which accounts for the three aforementioned notions, is formulated. More recently, the same authors have extended their work to enable dealing with the notion of degree of conflict, in contrast to merely conflicting or non-conflicting information [184]. Nonetheless, current formalism is still not complete as there are some foreseen notions of the STANAG recommendations, such as total ignorance about the reliability of the information source, that are not being considered. Another important aspect related to input information quality, which is largely ignored, is the rate at which it is provided to the fusion system. The information rate is a function of many factors, including the revisit rate of the sensors, the rate at which data sets are communicated, and also the quality of the communication link [185]. The effect of information rate is particularly important in decentralized fusion settings where imperfect communication is common.
- *Assessing the performance of the fusion system:* the performance of fusion systems itself is computed and compared using a specific set of measures referred to as measures of performance (MOP). The literature work on MOP is rather extensive and includes a wide variety of measures. The choice of the specific MOP(s) of interest depends on the characteristics of the fusion system. For instance, there is more to evaluate in a multiple sensor system than there is in a single sensor system. Furthermore, in the case of multi-target problems, the data/track association part of the system also needs to be evaluated along wih the estimation part. The commonly used MOPs may be broadly categorized into the metrics computed for each target and metrics computed over an ensemble of targets. Some of the MOPs belonging to the former category are track accuracy, track covariance consistency, track jitter, track estimate bias, track purity, and track continuity. Example of measures in the latter category are average number of missed targets, average number of extra targets, average track initiation time, completeness history, and cross-platform commonality history [186,187]. There are also other less popular measures related to the discrimination and/or classification capability of the fusion system that can be useful to collect in some applications. Aside from the conventional approaches for performance measurement, there is some notable work on development of MOPs for multi-target fusion systems within the Finite Set theory framework [188,189]. The key observation is that a multi-target system is fundamentally different from a single-target system. In the former case, the system state is indeed a finite set of vectors rather than a single vector. This is due to the appearance/disappearance of targets, which leads to the number of states varying with time. In addition, it is more natural to mathematically represent the collection of states as a finite set, as the order in which the states are listed has no physical significance [190]. This approach is especially useful in fusion application where the number of targets is not known and has to be inferred along with their positions. Finally, it is worth pointing out some of the fusion evaluation tools and testbeds that have recently become available. The Fusion Performance Analysis (FPA) tool from Boeing is a software that enables compuatation of technical performance measures (TPM) for virtually any fusion system. It is developed in Java (thus is platform-independent) and implements numerous TPMs in three main categories, namely, state estimation, track quality, and discrimination [191]. Another interesting recent development is the multisensor-multitarget tracking testbed [192], which has been recently introduced and is the first step towards the realization of a state-of-the-art testbed for evaluation of large-scale distributed fusion systems.

To the best of our knowledge, there is no standard and well-established evaluation framework to assess the performance of data fusion algorithms. Most of the work is being done in simulation and based on sometimes idealized assumption(s), which make it difficult to predict how the algorithm would perform in real-life applications. A recent review of literature on data fusion performance evaluation is presented in [193], where the challenging aspects of data fusion performance evaluation, in practice, are discussed. Having analyzed over 50 of the related literature work, it has been shown that only a very few (i.e. about 6%) of the surveyed research work, treats the fusion evaluation problem from a practical perspective. Indeed, it is demonstrated that most of the existing work is focused on performing evaluation in simulation or unrealistic test environments, which is substantially different from practical cases. Some of the major challenging problems of fusion evaluation in practice, which are usually ignored in the literature, are the following:

1. The ground truth is not usually known in practice, yet many of the currently used performance measures require knowledge of the ground truth.
2. Performance has different, possibly conflicting, dimensions that are difficult to capture in one comprehensive and unified measure. For instance, one can argue that performance evaluation should be multi-faceted, i.e. not only the extent of achieving the fusion goals should be measured, but also the amount of effort/resources spent to accomplish these goals should be considered.
3. In order to be a fair indicator of fusion performance, the performance measures might need to be adapted over time or according to the given context/situation.

The first issue is the most common and serious issue, especially within the image fusion community. One potential solution is to develop the so-called objective performance measures, i.e. independent from the ground truth or human subjective evaluation. Nonetheless, there is very little work done in this regard.

[1] North Atlantic Treaty Organization.

The second issue reflects the fact that it may be very difficult to devise a unified MOP to capture all aspects of system performance in a comprehensive manner. This is mainly due to the existence of trade-offs between competing performance aspects. For instance, the precision vs. recall trade-off is well-acknowledged in the fusion community. Thus, a comprehensive MOP might become too abstract and fail to properly reveal all dimensions of system performance [194]. An alternative is to deploy a set of MOPs as needed by the given application.

Finally, the third issue represents the importance of taking into consideration the specific situation or context under which the fusion system is being evaluated. This is important as the more difficult the evaluation scenario, the more challenging it becomes for the fusion system to maintain the desired performance level. Based on this observation, some researchers have proposed metrics to enable quantification of the complexity of the evaluation scenario(s), which is typically referred to as context metric [195]. A similar alternative approach is the so-called goal dependent performance metrics that are capable of adjusting themselves to the circumstances defined by context at a certain moment in time [193,196] incorporating mechanisms such as self-learning [197].

Regarding the above discussions, there appears to be a serious need for further research on development and standardizing measures of performance applicable to the practical evaluaion of data fusion systems.

## 6. Conclusion

This paper presented a critical review of data fusion state of the art methodologies. Data fusion is a multi-disciplinary research field with a wide range of potential applications in areas such as defense, robotics, automation and intelligent system design, and pattern recognition. This has been and will continue to act as the driving force behind the ever-increasing interest in research community in developing more advanced data fusion methodologies and architectures. We introduced a new *data centric* taxonomy of data fusion methodologies, and explored challenging aspects and associated theoretical frameworks and algorithms existing in each of the categories. Furthermore, several of the emerging areas of research in the data fusion community were presented.

Based on this exposition, it is clear that research on data fusion systems is becoming more and more common-place. There are a number of areas in the data fusion community that will most likely be highly active in the near future. For instance, the ever-increasing demand for data fusion on extremely large scales, such as sensor networks and the Web, will drive intense research on highly scalable data fusion algorithms based on distributed architectures. In addition, the availability and abundance of non-conventional data in the form of human-generated reports or Web documents will lead to the development of new and powerful fusion frameworks capable of processing a wide variety of data forms. Such fusion frameworks could potentially be realized by exploiting strong mathematical tools for modeling imperfect data, such as random set theory. With data fusion algorithms extending their application from the military domain to many other fields such as robotics, sensor networks, and image processing, the need for standard fusion evaluation protocols applicable independent of the given application domain will grow more than ever. As a result, the fusion community will be driven towards development and widespread adoption of such procotols in the future. This trend is also anticipated to motivate more extensive research on topics related to the performance of data fusion systems in practice such as fusion security and belief reliability. It is our hope for this paper to serve as a review of advances in the breadth of work on sensor data fusion, and to provide the data fusion community with a picture of the contemporary state of fusion research.

## References

[1] I. Bloch, Information combination operators for data fusion: a comparative review with classification, IEEE Transactions on SMC: Part A 26 (1) (1996) 52–67.
[2] D.L. Hall, J. Llinas, An introduction to multisensor fusion, Proceedings of the IEEE 85 (1) (1997) 6–23.
[3] D. Smith, S. Singh, Approaches to multisensor data fusion in target tracking: a survey, IEEE Transactions on Knowledge and Data Engineering 18 (12) (2006) 1696–1710.
[4] A.A. Goshtasby, S. Nikolov, Image fusion: advances in the state of the art, Information Fusion 8 (2) (2007) 114–118.
[5] I. Corona, G. Giacinto, C. Mazzariello, F. Roli, C. Sansone, Information fusion for computer security: state of the art and open issues, Information Fusion 10 (4) (2009) 274–284.
[6] H. Wache, T. Vögele, U. Visser, H. Stuckenschmidt, G. Schuster, H. Neumann, S. Hübner, Ontology-based integration of information – a survey of existing approaches, in: Proc. of the IJCAI – Workshop on Ontologies and Information Sharing, 2001, pp. 108–117.
[7] G.L. Rogova, V. Nimier, Reliability in information fusion: literature survey, in: Proc. of the International Conference on Information Fusion, 2004, pp. 1158–1165.
[8] J.T. Yao, V.V. Raghavan, Z. Wu, Web information fusion: a review of the state of the art, Information Fusion 9 (4) (2008) 446–449.
[9] F.E. White, Data Fusion Lexicon, Joint Directors of Laboratories, Technical Panel for C3, Data Fusion Sub-Panel, Naval Ocean Systems Center, San Diego, 1991.
[10] L.A. Klein, Sensor and Data Fusion Concepts and Applications, second ed., Society of Photo-optical Instrumentation Engineers (SPIE), Bellingham, WA, 1999.
[11] H. Boström, S.F. Andler, M. Brohede, R. Johansson, A. Karlsson, J. van Laere, L. Niklasson, M. Nilsson, A. Persson, T. Ziemke, On the Definition of Information Fusion as a Field of Research, Informatics Research Centre, University of Skövde, Tech. Rep. HS-IKI-TR-07-006, 2007.
[12] E.L. Walts, Data fusion for C3I: a tutorial, in: Command, Control, Communications Intelligence (C3I) Handbook, EW Communications Inc., Palo Alto, CA, 1986, pp. 217–226.
[13] A.N. Steinberg, C.L. Bowman, F.E. White, Revisions to the JDL data fusion model, in: Proc. of the SPIE Conference on Sensor Fusion: Architectures, Algorithms, and Applications III, 1999, pp. 430–441.
[14] J. Llinas, C. Bowman, G. Rogova, A. Steinberg, E. Waltz, F.E. White, Revisiting the JDL data fusion model II, in: Proc. of the International Conference on Information Fusion, 2004, pp. 1218–1230.
[15] B.V. Dasarathy, Decision Fusion, IEEE Computer Society Press, Los Alamitos, CA, 1994.
[16] I.R. Goodman, R.P.S. Mahler, H.T. Nguyen, Mathematics of Data Fusion, Kluwer Academic Publishers, Norwell, MA, 1997.
[17] M.M. Kokar, J.A. Tomasik, J. Weyman, Formalizing classes of information fusion systems, Information Fusion 5 (3) (2004) 189–202.
[18] M. Kumar, D.P. Garg, R.A. Zachery, A generalized approach for inconsistency detection in data fusion from multiple sensors, in: Proc. of the American Control Conference, 2006, pp. 2078–2083.
[19] P. Smets, Analyzing the combination of conflicting belief functions, Information Fusion 8 (4) (2007) 387–412.
[20] R.P.S. Mahler, statistics 101 for multisensor, multitarget data fusion, IEEE Aerospace and Electronic Systems Magazine 19 (1) (2004) 53–64.
[21] R. Joshi, A.C. Sanderson, Multisensor Fusion: A Minimal Representation Framework, World Scientific, 1999.
[22] X.L. Dong, L. Berti-Equille, D. Srivastava, Truth discovery and copying detection in a dynamic world, Journal Proceedings of the VLDB Endowment 2 (1) (2009) 562–573.
[23] Y. Zhu, E. Song, J. Zhou, Z. You, Optimal dimensionality reduction of sensor data in multisensor estimation fusion, IEEE Transactions on Signal Processing 53 (5) (2005) 1631–1639.
[24] B.L. Milenova, M.M. Campos, Mining high-dimensional data for information fusion: a database-centric approach, in: Proc. of International Conference on Information Fusion, 2005, pp. 638–645.
[25] P. Krause, D. Clark, Representing Uncertain Knowledge: An Artificial Intelligence Approach, Kluwer Academic Publishers, Norwell, MA, 1993.
[26] P. Smets, Imperfect information: imprecision and uncertainty, in: A. Motro, P. Smets (Eds.), Uncertainty Management in Information Systems: From Needs to Solutions, Kluwer Academic Publishers., Norwell, MA, 1997, pp. 225–254.
[27] G.J. Klir, M.J. Wierman, Uncertainty-Based Information: Elements of Generalized Information Theory, second ed., Physica-Verlag HD, New York, 1999.
[28] D. Dubois, H. Prade, Formal representations of uncertainty, in: D. Bouyssou, D. Dubois, M. Pirlot, H. Prade (Eds.), Decision-Making Process-Concepts and Methods, ISTE & Wiley, London, 2009, pp. 85–156.
[29] M.C. Florea, A.L. Jousselme, E. Bosse, Fusion of Imperfect Information in the Unified Framework of Random Sets Theory: Application to Target Identification, Defence R&D Canada, Valcartier, Tech. Rep. ADA475342, 2007.

Please cite this article in press as: B. Khaleghi et al., Multisensor data fusion: A review of the state-of-the-art, Informat. Fusion (2011), doi:10.1016/j.inffus.2011.08.001

[30] J. Komorowski, Z. Pawlak, L. Polkowski, A. Skowron, Rough sets: a tutorial, in: S.K. Pal, A. Skowron (Eds.), Rough Fuzzy Hybridization: A New Trend in Decision Making, Springer, Singapore, 1999, pp. 1–98.
[31] F.K.J. Sheridan, A survey of techniques for inference under uncertainty, Artificial Intelligence Review 5 (1–2) (1991) 89–119.
[32] H.F. Durrant-Whyte, T.C. Henderson, Multisensor data fusion, in: B. Siciliano, O. Khatib (Eds.), Handbook of Robotics, Springer, 2008, pp. 585–610.
[33] L.A. Zadeh, Fuzzy sets, Information and Control 8 (3) (1965) 338–353.
[34] L.A. Zadeh, Fuzzy sets as a basis for a theory of possibility, Fuzzy Sets and Systems 1 (1) (1978) 3–28.
[35] Z. Pawlak, Rough Sets: Theoretical Aspects of Reasoning about Data, Kluwer Academic Publishers, Norwell, MA, 1992.
[36] G. Shafer, A Mathematical Theory of Evidence, Princeton University Press, 1976.
[37] D. Dubois, H. Prade, Rough fuzzy sets and fuzzy rough sets, International Journal of General Systems 17 (2–3) (1990) 191–209.
[38] J. Yen, Generalizing the Dempster–Shafer theory to fuzzy sets, IEEE Transactions on SMC 20 (3) (1990) 559–570.
[39] R.P.S. Mahler, Statistical Multisource-Multitarget Information Fusion, Artech House, Boston, MA, 2007.
[40] G. Welch, G. Bishop, An Introduction to the Kalman Filter, Department of Computer Science, University of North Carolina, Tech. Rep. TR-95-041, 1995.
[41] S.J. Julier, J.K. Uhlmann, A new extension of the Kalman filter to nonlinear systems, in: International Symposium on Aerospace/Defense Sensing, Simulation and Controls, 1997, pp. 182–193.
[42] L.D. Stone, T.L. Corwin, C.A. Barlow, Bayesian Multiple Target Tracking, Artech House Inc., Norwood, MA, 1999.
[43] A. Doucet, N. de Freitas, N. Gordon, Sequential Monte Carlo Methods in Practice (Statistics for Engineering and Information Science), Springer, New York, 2001.
[44] B.A. Berg, Markov Chain Monte Carlo Simulations and Their Statistical Analysis, World Scientific, Singapore, 2004.
[45] D. Crisan, A. Doucet, A survey of convergence results on particle filtering methods for practitioners, IEEE Transactions on Signal Processing 50 (3) (2002) 736–746.
[46] N.J. Gordon, D.J. Salmond, A.F.M. Smith, Novel approach to nonlinear/non-Gaussian Bayesian state estimation, IEE Proceedings – F 140 (2) (1993) 107–113.
[47] M.K. Pitt, N. Shephard, Filtering via simulation: auxiliary particle filters, Journal of the American Statistical Association 94 (446) (1999) 590–599.
[48] N. Metropolis, S. Ulam, The Monte Carlo method, Journal of American Statistics Association 44 (247) (1949) 335–341.
[49] W.K. Hastings, Monte Carlo sampling methods using markov chains and their applications, Biometrika 57 (1) (1970) 97–109.
[50] G. Casella, E.I. George, Explaining the Gibbs sampler, The American Statistician 46 (3) (1992) 167–174.
[51] J.S. Rosenthal, Parallel computing and Monte Carlo algorithms, Far East Journal of Theoretical Statistics 4 (2000) 207–236.
[52] M.K. Cowles, B.P. Carlin, Markov Chain Monte Carlo convergence diagnostics: a comparative review, Journal of American Statistics Accosication 91 (434) (1996) 883–904.
[53] A.P. Dempster, A generalization of Bayesian inference (with discussion), Journal of the Royal Statistical Society Series B 30 (2) (1968) 205–247.
[54] T.D. Garvey, J.D. Lowrance, M.A. Fischler, An inference technique for integrating knowledge from disparate sources, in: Proc. of the International Joint Conference on Artificial Intelligence, 1981, pp. 319–325.
[55] B.R. Bracio, W. Horn, D.P.F. Moller, Sensor fusion in biomedical systems, in: Proc. of Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 1997, pp. 1387–1390.
[56] J.A. Barnett, Computational methods for a mathematical theory of evidence, in: Proc. of the International Joint Conference on Artificial Intelligence, 1981, pp. 868–875.
[57] J. Gordon, E.H. Shortliffe, A method for managing evidential reasoning in a hierarchical hypothesis space, Artificial Intelligence 26 (3) (1985) 323–357.
[58] A. Benavoli, B. Ristic, A. Farina, M. Oxenham, L. Chisci, An approach to threat assessment based on evidential networks, in: Proc. of the International Conference on Information Fusion, 2007, pp. 1–8.
[59] H.H.S. Ip, H. Tang, Parallel evidence combination on a SB-tree architecture, in: Proc. of the Australian and New Zealand Conference on Intelligent Information Systems, 1996, pp. 31–34.
[60] M. Bauer, Approximation algorithms and decision making in the Dempster–Shafer theory of evidence – an empirical study, International Journal of Approximate Reasoning 17 (2–3) (1997) 217–237.
[61] T. Denoeux, A.B. Yaghlane, Approximating the combination of belief functions using the fast Möbius transform in a coarsened frame, International Journal of Approximate Reasoning 31 (1–2) (2002) 77–101.
[62] M. Oxenham, The effect of finite set representations on the evaluation of Dempster's rule of combination, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[63] P.P. Shenoy, G. Shafer, Axioms for probability and belief-function propagation, in: R.R. Yager, L. Liu (Eds.), Classic Works of the Dempster–Shafer Theory of Belief Functions, Springer, Berlin/Heidel-Berg, 2008, pp. 499–528.
[64] D. Dubois, H. Prade, Possibility theory and data fusion in poorly informed environments, Control Engineering Practice 2 (5) (1994) 811–823.
[65] P.J. Escamilla-Ambrosio, N. Mort, Hybrid Kalman filter-fuzzy logic adaptive multisensor data fusion architectures, in: Proc. of the IEEE Conference on Decision and Control, 2003, pp. 5215–5220.
[66] J.Z. Sasiadek, P. Hartana, Sensor data fusion using Kalman filter, in: Proc. of the International Conference on Information Fusion, 2000, pp. WED5/19–WED5/25.
[67] H. Zhu, O. Basir, A novel fuzzy evidential reasoning paradigm for data fusion with applications in image processing, Soft Computing Journal – A Fusion of Foundations, Methodologies and Applications 10 (12) (2006) 1169–1180.
[68] D. Dubois, H. Prade, Possibility Theory: An Approach to Computerized Processing of Uncertainty, Plenum Press, 1988.
[69] D. Dubois, H. Prade, Possibility theory in information fusion, in: Proc. of the International Conference on Information Fusion, 2000, pp. PS6–PS19.
[70] S. Destercke, D. Dubois, E. Chojnacki, Possibilistic information fusion using maximal coherent subsets, IEEE Transactions on Fuzzy Systems 17 (1) (2009) 79–92.
[71] D. Dubois, H. Prade, When upper probabilities are possibility measures, Fuzzy Sets and Systems 49 (1) (1992) 65–74.
[72] H. Borotschnig, L. Paletta, M. Prantl, A. Pinz, Comparison of probabilistic, possibilistic and evidence theoretic fusion schemes for active object recognition, Computing 62 (4) (1999) 293–319.
[73] S. Benferhat, C. Sossai, Reasoning with multiple-source information in a possibilistic logic framework, Information Fusion 7 (1) (2006) 80–96.
[74] Z. Pawlak, A. Skowron, Rudiments of rough sets, Information Sciences 177 (1) (2007) 3–27.
[75] L. Yong, X. Congfu, P. Yunhe, A new approach for data fusion: implement rough set theory in dynamic objects distinguishing and tracing, in: Proc. of the IEEE International Conference on SMC, 2004, pp. 3318–3322.
[76] J.F. Peters, S. Ramanna, A. Skowron, J. Stepaniuk, Z. Suraj, Sensor fusion: a rough granular approach, in: Proc. of the IFSA World Congress and 20th NAFIPS International Conference, 2001, pp. 1367–1371.
[77] W. Haijun, C. Yimin, Sensor data fusion using rough set for mobile robots system, in: Proc. of the IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications, 2006, pp. 1–5.
[78] R.R. Yager, Generalized probabilities of fuzzy events from fuzzy belief structures, Information Sciences 28 (1) (1982) 45–62.
[79] O. Basir, F. Karray, Z. Hongwei, Connectionist-based Dempster–Shafer evidential reasoning for data fusion, IEEE Transactions on Neural Networks 6 (6) (2005) 1513–1530.
[80] D.S. Yeung, C. Degang, E.C.C. Tsang, J.W.T. Lee, X. Wang, On the generalization of fuzzy rough sets, IEEE Transactions on Fuzzy Systems 13 (3) (2005) 343–361.
[81] T. Guan, B. Feng, Rough fuzzy integrals for information fusion and classification, Lecture Notes in Computer Science 3066 (2004) 362–367.
[82] D.G. Kendall, Foundations of a theory of random sets, in: E.F. Hardings, D.G. Kendall (Eds.), Stochastic Geometry, J. Wiley, 1974, pp. 322–376.
[83] V. Kreinovich, Random sets unify, explain, and aid known uncertainty methods in expert systems, in: J. Goutsias, R.P.S. Mahler, H.T. Nguyen (Eds.), Random Sets: Theory and Applications, Springer-Verlag, 1997, pp. 321–345.
[84] S. Mori, Random sets in data fusion. Multi-object state-estimation as a foundation of data fusion theory, in: J. Goutsias, R.P.S. Mahler, H.T. Nguyen (Eds.), Random Sets: Theory and Applications, Springer-Verlag, 1997, pp. 185–207.
[85] R.P.S. Mahler, Random sets: unification and computation for information fusion – a retrospective assessment, in: Proc. of the International Conference on Information Fusion, 2004, pp. 1–20.
[86] R.P.S. Mahler, PHD filters of higher order in target number, IEEE Transactions on Aerospace and Electronic Systems 43 (4) (2007) 1523–1543.
[87] B.T. Vo, B.N. Vo, A. Cantoni, The cardinalized probability hypothesis density filter for linear Gaussian multi-target models, in: Proc. of the Annual Conference on Information Sciences and Systems, 2006, pp. 681–686.
[88] B.T. Vo, B.N. Vo, A. Cantoni, Analytic implementations of the cardinalized probability hypothesis density filter, IEEE Transactions on Signal Processing 55 (7) (2007) 3553–3567.
[89] B.N. Vo, W.K. Ma, The Gaussian mixture probability hypothesis density filter, IEEE Transactions on Signal Processing 54 (11) (2006) 4091–4104.
[90] B.N. Vo, S. Singh, A. Doucet, Sequential Monte Carlo methods for multi-target filtering with random finite sets, IEEE Transactions on Aerospace and Electronic Systems 41 (4) (2005) 1224–1245.
[91] K. Panta, B.N. Vo, S. Singh, A. Doucet, Probability hypothesis density versus multiple hypothesis tracking, in: Proc. of the SPIE Conference on Signal Processing, Sensor Fusion and Target Recognition, 2004, pp. 284–295.
[92] R.P.S. Mahler, A survey of PHD filter and CPHD filter implementations, in: Proc. of the SPIE Conference on Signal Processing, Sensor Fusion, and Target Recognition, 2007, pp. 65670O1–65670O12.
[93] D. Angelosante, E. Biglieri, M. Lops, Multiuser detection in a dynamic environment: joint user identification and parameter estimation, in: Proc. of the IEEE International Symposium on Information Theory, 2007, pp. 2071–2075.
[94] M. Maehlisch, R. Schweiger, W. Ritter, K. Dietmayer, Multisensor vehicle tracking with the probability hypothesis density filter, in: Proc. of the International Conference on Information Fusion, 2006, pp. 1–8.
[95] R.P.S. Mahler, Sensor management with non-ideal sensor dynamics, in: Proc. of the International Conference on Information fusion, 2004, pp. 783–790.

[96] B. Khaleghi, A. Khamis, F. Karray, Random finite set theoretic based soft/hard data fusion with application for target tracking, in: Proc. of the IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems, 2010, pp. 50–55.
[97] X. Mingge, H. You, H. Xiaodong, S. Feng, Image fusion algorithm using rough sets theory and wavelet analysis, in: Proc. of the International Conference on Signal Processing, 2004, pp. 1041–1044.
[98] S.J. Julier, J.K. Uhlmann, A non-divergent algorithm in the presence of unknown correlation, in: Proc. of the American Control Conference, 1997, pp. 2369–2373.
[99] A. Makarenko, A. Brooks, T. Kaupp, H.F. Durrant-Whyte, F. Dellaert, Decentralised data fusion: a graphical model approach, in: Proc. of the International Conference on Information Fusion, 2009, pp. 545–554.
[100] P.S. Maybeck, Stochastic Models, Estimation and Control, Academic Press, New York, 1979.
[101] J.K. Uhlmann, S.J. Julier, H.F. Durrant-Whyte, A Culminating Advance in the Theory and Practice of Data Fusion, Filtering and Decentralized Estimation, Covariance Intersection Working Group, Tech. Rep., 1997.
[102] C.Y. Chong, S. Mori, K.C. Chang, Distributed multitarget multisensor tracking, in: Y. Bar-Shalom (Ed.), Multitarget-Multisensor Tracking: Advanced Applications, Artech House, Norwood, MA, 1990, pp. 247–295.
[103] K.C. Chang, C.Y. Chong, S. Mori, On scalable distributed sensor fusion, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[104] A.D. Marrs, C.M. Reed, A.R. Webb, H.C. Webber, Data Incest and Symbolic Information Processing, United Kingdom Defence Evaluation and Research Agency, Tech. Rep., 1999.
[105] S.P. McLaughlin, R.J. Evans, V. Krishnamurthy, Data incest removal in a survivable estimation fusion architecture, in: Proc. of the International Conference on Information Fusion, 2003, pp. 229–236.
[106] L.Y. Pao, M. Kalandros, Algorithms for a class of distributed architecture tracking, in: Proc. of the American Control Conference, 1997, pp. 1434–1438.
[107] S.P. McLaughlin, R.J. Evans, V. Krishnamurthy, A graph theoretic approach to data incest management in network centric warfare, in: Proc. of the International Conference on Information Fusion, 2005, pp. 1162–1169.
[108] T. Brehard, V. Krishnamurthy, Optimal data incest removal in Bayesian decentralized estimation over a sensor network, in: IEEE International Conference on Acoustics, Speech and Signal Processing, 2007, pp. III173–III176.
[109] W. Khawsuk, L.Y. Pao, Decorrelated state estimation for distributed tracking of interacting targets in cluttered environments, in: Proc. of the American Control Conference, 2002, pp. 899–904.
[110] M.B. Hurley, An information theoretic justification for covariance intersection and its generalization, in: Proc. of the International Conference on Information Fusion, 2002, pp. 505–511.
[111] L. Chen, P.O. Arambel, R.K. Mehra, Estimation under unknown correlation: covariance intersection revisited, IEEE Transactions on Automatic Control 47 (11) (2002) 1879–1882.
[112] W. Niehsen, Information fusion based on fast covariance intersection filtering, in: Proc. of the International Conference on Information Fusion, 2002, pp. 901–904.
[113] D. Franken, A. Hupper, Improved fast covariance intersection for distributed data fusion, in: Proc. of the International Conference on Information Fusion, 2005, pp. 154–160.
[114] A.R. Benaskeur, Consistent fusion of correlated data sources, in: Proc. of IEEE Annual Conference of the Industrial Electronics Society, 2002, pp. 2652–2656.
[115] Y. Zhou, J. Li, Robust decentralized data fusion based on internal ellipsoid approximation, in: Proc. of World Congress of the International Federation of Automatic Control, 2008, pp. 9964–9969.
[116] W.J. Farrell, C. Ganesh, Generalized chernoff fusion approximation for practical distributed data fusion, in: Proc. of the International Conference on Information Fusion, 2009, pp. 555–562.
[117] Z. Djurovic, B. Kovacevic, QQ-plot approach to robust Kalman filtering, International Journal of Control 61 (4) (1995) 837–857.
[118] S.J. Wellington, J.K. Atkinson, R.P. Sion, Sensor validation and fusion using the Nadaraya-Watson statistical estimator, in: Proc. of the International Conference on Information Fusion, 2002, pp. 321–326.
[119] P.H. Ibarguengoytia, L.E. Sucar, V. Vadera, Real time intelligent sensor validation, IEEE Transactions on Power Systems 16 (4) (2001) 770–775.
[120] J. Frolik, M. Abdelrahman, P. Kandasamy, A confidence-based approach to the self-validation, fusion and reconstruction of quasiredundant sensor data, IEEE Transactions on Instrumentation and Measurement 50 (6) (2001) 1761–1769.
[121] M. Kumar, D.P. Garg, R.A. Zachery, A method for judicious fusion of inconsistent multiple sensor data, IEEE Sensors Journal 7 (5) (2007) 723–733.
[122] M. Kumar, D. Garg, R. Zachery, Stochastic adaptive sensor modeling and data fusion, in: Proc. of the SPIE Conference on Smart Structures and Materials: Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems, 2006, pp. 100–110.
[123] U. Orguner, F. Gustafsson, Storage efficient particle filters for the out of sequence measurement problem, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[124] S.S. Blackman, R. Popoli, Design and Analysis of Modern Tracking Systems, Artech House, Berlin, 1999.
[125] Y. Bar-Shalom, Update with out-of-sequence measurements in tracking: exact solution, IEEE Transactions on Aerospace and Electronic Systems 38 (3) (2002) 769–777.
[126] M. Mallick, S. Coraluppi, C. Carthel, Advances in asynchronous and decentralized estimation, in: Proc. of the IEEE Aerospace Conference, 2001, pp. 4/1873–4/1888.
[127] K. Zhang, X.R. Li, Y. Zhu, Optimal update with out-of-sequence measurements for distributed filtering, in: Proc. of the International Conference on Information Fusion, 2002, pp. 1519–1526.
[128] K. Zhang, X.R. Li, Y. Zhu, Optimal update with out-of-sequence measurements, IEEE Transactions on Signal Processing 53 (6) (2005) 1992–2004.
[129] Y. Bar-Shalom, H. Chen, M. Mallick, One-step solution for the multistep out-of-sequence measurement problem in tracking, IEEE Transactions on Aerospace and Electronic Systems 40 (1) (2004) 27–37.
[130] Y. Anxi, L. Diannong, H. Weidong, D. Zhen, A unified out-of-sequence measurements filter, in: Proc. of the IEEE International Radar Conference, 2005, pp. 453–458.
[131] M. Mallick, J. Krant, Y. Bar-Shalom, Multi-sensor multi-target tracking using out-of-sequence measurements, in: Proc. of the International Conference on Information Fusion, 2002, pp. 135–142.
[132] S.R. Maskell, R.G. Everitt, R. Wright, M. Briers, Multi-target out-of-sequence data association: tracking using graphical models, Information Fusion 7 (4) (2006) 434–447.
[133] S. Challa, J.A. Legg, Track-to-track fusion of out-of-sequence tracks, in: Proc. of the International Conference on Information Fusion, 2002, pp. 919–926.
[134] A. Novoselsky, S.E. Sklarz, M. Dorfan, Track to track fusion using out-of-sequence track information, in: Proc. of the International Conference on Information Fusion, 2007, pp. 1–5.
[135] L.A. Zadeh, Review of "a mathematics theory of evidence", AI Magazine 5 (3) (1984) 81–83.
[136] M.C. Florea, A.L. Jousselme, E. Bosse, D. Grenier, Robust combination rules for evidence theory, Information Fusion 10 (2) (2009) 183–197.
[137] R.R. Yager, On the Dempster–Shafer framework and new combination rules, Information Sciences 41 (2) (1987) 93–137.
[138] P. Smets, The combination of evidence in the transferable belief model, IEEE Transactions on Pattern Analysis and Machince Intelligence 12 (5) (1990) 447–458.
[139] J. Dezert, Foundations for a new theory of plausible and paradoxical reasoning, Information Security 9 (2002) 13–57.
[140] E. Lefevre, O. Colot, P. Vannoorenberghe, Belief function combination and the conflict management, Information Fusion 3 (2) (2002) 149–162.
[141] F. Voorbraak, On the justification of Dempster's rule of combination, Artificial Intelligence 48 (2) (1991) 171–197.
[142] R. Haenni, Are alternatives to Dempster's rule of combination real alternatives? Comments on "About the belief combination and the conflict management problem" – Lefevre et al., Information Fusion 3 (3) (2002) 237–239.
[143] J. Dezert, A. Martin, F. Smarandache, Comments on "A new combination of evidence based on compromise" by K. Yamada, Fuzzy Sets and Systems 160 (2009) 853–855.
[144] J.K. Uhlmann, Covariance consistency methods for fault-tolerant distributed data fusion, Information Fusion 4 (3) (2003) 201–215.
[145] S. Maskell, A Bayesian approach to fusing uncertain, imprecise and conflicting information, Information Fusion 9 (2) (2008) 259–277.
[146] F. Rheaume, A.R. Benaskeur, Forward prediction-based approach to target-tracking with out-of-sequence measurements, in: Proc. of the IEEE Conference on Decision and Control, 2008, pp. 1326–1333.
[147] D.L. Hall, M. McNeese, J. Llinas, T. Mullen, A framework for dynamic hard/soft fusion, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[148] M.A. Pravia, R.K. Prasanth, P.O. Arambel, C. Sidner, C.Y. Chong, Generation of a fundamental data set for hard/soft information fusion, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[149] M.A. Pravia, O. Babko-Malaya, M.K. Schneider, J.V. White, C.Y. Chong, Lessons learned in the creation of a data set for hard/soft information fusion, in: Proc. of the International Conference on Information Fusion, 2009, pp. 2114–2121.
[150] K. Premaratne, M.N. Murthi, J. Zhang, M. Scheutz, P.H. Bauer, A Dempster–Shafer theoretic conditional approach to evidence updating for fusion of hard and soft data, in: Proc. of the International Conference on Information Fusion, 2009, pp. 2122–2129.
[151] A. Auger, J. Roy, Expression of uncertainty in linguistic data, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[152] D.L. Hall, M.D. McNeese, D.B. Hellar, B.J. Panulla, W. Shumaker, A cyber infrastructure for evaluating the performance of human centered fusion, in: Proc. of the International Conference on Information Fusion, 2009, pp. 1257–1264.
[153] K. Sambhoos, J. Llinas, E. Little, Graphical methods for real-time fusion and estimation with soft message data, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[154] G. Ferrin, L. Snidaro, S. Canazza, G.L. Foresti, Soft data issues in fusion of video surveillance, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[155] S. Challa, T. Gulrez, Z. Chaczko, T.N. Paranesha, Opportunistic information fusion: a new paradigm for next generation networked sensing systems, in: Proc. of the International Conference on Information Fusion, 2005, pp. 720–727.

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[156] C. Wu, H. Aghajan, Model-based human posture estimation for gesture analysis in an opportunistic fusion smart camera network, in: Proc. of the IEEE Conference on Advanced Video and Signal Based Surveillance, 2007, pp. 453–458.
[157] R. Al-Hmouz, S. Challa, Optimal placement for opportunistic cameras using genetic algorithm, in: Proc. of the International Conference on Intelligent Sensors, Sensor Networks and Information Processing, 2005, pp. 337–341.
[158] L. Hong, Adaptive data fusion, in: Proc. of the IEEE International Conference on SMC, 1991, pp. 767–772.
[159] G. Loy, L. Fletcher, N. Apostoloff, A. Zelinsky, An adaptive fusion architecture for target tracking, in: Proc. of the IEEE International Conference on Automatic Face and Gesture Recognition, 2002, pp. 261–266.
[160] P.J. Escamilla-Ambrosio, N. Mort, Hybrid Kalman filter-fuzzy logic adaptive multisensor data fusion architectures, in: Proc. of the IEEE Conference on Decision and Control, 2003, pp. 5215–5220.
[161] A.D. Tafti, N. Sadati, Novel adaptive Kalman filtering and fuzzy track fusion approach for real time applications, in: Proc. of the IEEE Conference on Industrial Electronics and Applications, 2008, pp. 120–125.
[162] H.E. Soken, C. Hajiyev, Adaptive unscented Kalman filter with multiple fading factors for pico satellite attitude estimation, in: Proc. of the International Conference on Recent Advances in Space Technologies, 2009, pp. 541–546.
[163] X. Huang, S. Oviatt, Toward adaptive information fusion in multimodal systems, Lecture Notes in Computer Science 3869 (2006) 15–27.
[164] N. Ansari, E.S.H. Hou, B.O. Zhu, J.G. Chen, Adaptive fusion by reinforcement learning for distributed detection systems, IEEE Transactions on Aerospace and Electronic Systems 32 (2) (1996) 524–531.
[165] M.A. Hossain, P.K. Atrey, A. El-Saddik, Learning multisensor confidence using a reward-and-punishment mechanism, IEEE Transactions on Instrumentation and Measurement 58 (5) (2009) 1525–1534.
[166] G. Fabeck, R. Mathar, Kernel-based learning of decision fusion in wireless sensor networks, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–7.
[167] M.M. Kokar, K. Baclawski, H. Gao, Category theory-based synthesis of a higher-level fusion algorithm – an example, in: Proc. of the International Conference on Information fusion, 2006, pp. 1–8.
[168] V. Nimier, Introducing contextual information in multisensor tracking algorithms, in: Proc. of the International Conference on Processing and Management of Uncertainty in Knowledge-Based Systems, Advances in Intelligent Computing, 1994, pp. 595–604.
[169] B. Yu, K. Sycara, Learning the quality of sensor data in distributed decision fusion, in: Proc. of the International Conference on Information Fusion, 2006, pp. 1–8.
[170] F. Delmotte, L. Dubois, P. Borne, Context-dependent trust in data fusion within the possibility theory, in: Proc. of the IEEE International Conference on SMC, 1996, pp. 538–543.
[171] S.A. Sandri, D. Dubois, H.W. Kalfsbeek, Elicitation, assessment and pooling of expert judgments using possibility theory, IEEE Transactions on Fuzzy Systems 3 (3) (1995) 313–335.
[172] R. Haenni, S. Hartmann, Modeling partially reliable information sources: a general approach based on Dempster–Shafer theory, Information Fusion 7 (4) (2006) 361–379.
[173] Z. Elouedi, K. Mellouli, P. Smets, Assessing sensor reliability for multisensor data fusion within the transferable belief model, IEEE Transactions on SMC – Part B 34 (1) (2004) 782–787.
[174] E.J. Wright, K.B. Laskey, Credibility models for multi-source fusion, in: Proc. of the International Conference on Information Fusion, 2006, pp. 1–7.
[175] A. Karlsson, Dependable and Generic High-level Information Fusion – Methods and Algorithms for Uncertainty Management, School of Humanities and Informatics, University of Skövde, Sweden, Tech. Rep. HS-IKI-TR-07-003, 2007.
[176] M. Kefayati, M.S. Talebi, H.R. Rabiee, B.H. Khalaj, On secure consensus information fusion over sensor networks, in: Proc. of the IEEE International Conference on Computer Systems and Applications, 2007, pp. 108–115.
[177] M. Kefayati, M.S. Talebi, B.H. Khalaj, H.R. Rabiee, Secure consensus averaging in sensor networks using random offsets, in: Proc. of IEEE International Conference on Telecommunications, 2007, pp. 556–560.
[178] Y. Sang, H. Shen, Y. Inoguchi, Y. Tan, N. Xiong, Secure data aggregation in wireless sensor networks: a survey, in: Proc. of the IEEE International Conference on Parallel and Distributed Computing, Applications and Technologies, 2006, pp. 315–320.
[179] H. Alzaid, E. Foo, J.G. Nieto, Secure data aggregation in wireless sensor network: a survey, in: Proc. of the Australasian Information Security Conference, 2008, pp. 93–106.
[180] H. Chen, G. Chen, E.P. Blasch, P. Douville, K. Pham, Information theoretic measures for performance evaluation and comparison, in: Proc. of the International Conference on Information Fusion, 2009, pp. 874–881.
[181] L. Cholvy, Information evaluation in fusion: a case study, in: Proc. of the International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems, 2004, pp. 993–1000.
[182] STANAG 2022: Intelligence Reports, North Atlantic Treaty Organization (NATO), December 1992.
[183] V. Nimier, Information evaluation: a formalization of operational recommendations, in: Proc. of the International Conference on Information Fusion, 2004, pp. 1166–1171.
[184] L. Cholvy, Modelling information evaluation in fusion, in: Proc. of the International Conference on Information Fusion, 2007, pp. 1–6.
[185] A.E. Gelfand, C. Smith, M. Colony, C. Bowman, Performance evaluation of decentralized estimation systems with uncertain communications, in: Proc. of the International Conference on Information Fusion, 2009, pp. 786–793.
[186] O.E. Drummond, Methodologies for performance evaluation of multi-target multisensor tracking, in: Proc. of the SPIE Conference on Signal and Data Processing of Small Targets, 1999, pp. 355–369.
[187] R.L. Rothrock, O.E. Drummond, Performance metrics for multiple-sensor multiple-target tracking, in: Proc. of the SPIE Conference on Signal and Data Processing of Small Targets, 2000, pp. 521–531.
[188] T. Zajic, J.L. Hoffman, R.P.S. Mahler, Scientific performance metrics for data fusion: new results, in: Proc. of the SPIE Conferenec on Signal Processing, Sensor Fusion, and Target Recognition, 2000, pp. 172–182.
[189] D. Schuhmacher, B.T. Vo, B.N. Vo, A consistent metric for performance evaluation of multi-object filters, IEEE Transactions on Signal Processing 56 (8) (2008) 3447–3457.
[190] B.T. Vo, Random Finite Sets in Multi-object Filtering, Ph.D. Thesis, School of Electrical, Electronic and Computer Engineering, University of Western Australia, 2008.
[191] P. Jackson, J.D. Musiak, Boeing fusion performance analysis (FPA) tool, in: Proc. of the International Conference on Information Fusion, 2009, pp. 1444–1450.
[192] D. Akselrod, R. Tharmarasa, T. Kirubarajan, Z. Ding, T. Ponsford, Multisensor-multitarget tracking testbed, in: Proc. of the IEEE Symposium on Computational Intelligence for Security and Defense Applications, 2009, pp. 1–6.
[193] J. van Laere, Challenges for IF performance evaluation in practice, in: Proc. of the International Conference on Information Fusion, 2009, pp. 866–873.
[194] X.R. Li, Z. Duan, Comprehensive evaluation of decision performance, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[195] C.Y. Chong, Problem characterization in tracking/fusion algorithm evaluation, in: Proc. of the International Conference on Information Fusion, 2000, pp. 26–32.
[196] D. Schumacher, B.T. Vo, B.N. Vo, On performance evaluation of multi-object filters, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.
[197] C. Thomas, N. Balikrishnan, Modified evidence theory for performance enhancement of intrusion detection systems, in: Proc. of the International Conference on Information Fusion, 2008, pp. 1–8.

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