Reliability In Information Fusion: Literature Survey

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Abstract - *The success of information fusion is defined by the quality of knowledge produced by fusion processes, with the latter in turn depending on how well data are represented, how reliable and adequate the model of data uncertainty used, and how accurate and appropriate or applicable prior knowledge is. The majority of fusion operators is based on optimistic assumptions about reliability of sources and presumes that they are all reliable. At the same time, different sources may have different reliability and it is necessary to account for this fact to avoid decreasing in performance of fusion results. The objective of this paper is to discuss the principal concepts and strategies of incorporating reliability into classical fusion operators and to provide an overview of the main approaches used in the fusion literature.*

Keywords: Reliability, uncertainty model, fusion operators, uncertainty frameworks.

1 Introduction

Information Fusion is a field studying processes utilizing data coming from various input sources, techniques exploiting this data, a priori knowledge, and "known" models of uncertainty in various input sources to produce estimates and knowledge about objects and situations [1].

The success of information fusion depends on how well knowledge produced by fusion processes represents reality, which in term depends on how adequate data are, how good and adequate is the uncertainty model used, and how accurate, appropriate or applicable prior knowledge is.

The main body of the literature on information fusion concerns with building an adequate uncertainty model without paying much attention to the related problem of reliability of these models and fusion results. The majority of fusion operators is based on optimistic assumptions about reliability of the models producing beliefs and assumes that they are equally reliable and play a symmetrical role. At the same time, different models may have different reliability and it is necessary to account for this fact in order to avoid decreasing in performance of fusion results. Although the concept of reliability has been introduced, it allows for various interpretations and representations and is not yet well established [2]. The particular objective of this paper is to provide a discussion of definitions, issues, and a review of methodologies related to incorporation of belief reliability into data fusion.

The reminder of the paper is organized as follows. Section 2 defines the principal concept and strategies of using reliability in data fusion. Section 3 is an overview of methods explicitly utilizing reliability coefficients in the fusion methods designed in the Bayesian, evidence, and possibility frameworks. Section 4 presents the methods of modeling reliability coefficients. After a discussion on reliability of fusion results in Section 5, we will conclude in Section 6.

2 Using reliability in Fusion

2.1 Definition and role of reliability in fusion process

Most processes of parallel combination of beliefs described in the literature are concerned with adequate modeling of uncertainty, which is the result of noisy, imprecise, erroneous or ill-suited to the problem data, ambiguous observations, and incomplete and poorly defined prior knowledge [3]. The difficulty of modeling uncertainty stems from the difficulty of finding an adequate belief model. Most of the belief models are derived from neighborhood information according to a distance (see, e.g., [4,5]) or to likelihood functions (see, e.g., [6-8]). An inappropriate choice of metrics or poor estimation of the likelihood functions can provide an inadequate belief model and can lead to conflicting and unreliable beliefs to be combined. Moreover, beliefs can be model within different uncertainty frameworks and dealing with different sources may mean also dealing with different framework theories. In this paper we assume that beliefs to be combined are represented within the same uncertainty framework.

The process of modeling beliefs has always some limitations, and models are valid within a certain range. So, when combining information provided by many sources, we have to take into account the range and the limitations of the belief model used for each source. The most natural way to deal with this problem is to establish reliability of the beliefs computed within the framework of the model selected. This may be achieved by using reliability coefficients, which introduce the second level of uncertainty (uncertainty of evaluation of uncertainty) and represent a measure of the adequacy of the model used and the state of the environment observed. There are at least two approaches used for defining reliability as a higher order uncertainty [9]. In one of them reliability is understood as relative stability of the first order uncertainty. In this case reliability is often measured by the performance of each source, e.g., by the recognition or false alarm rates. Another approach to representing a higher level of uncertainty is to measure accuracy of predicted beliefs. Here reliability coefficients represent adequacy of each belief model to the reality. The discussion in this paper concentrates on this second notion of reliability.

Let $s_i, i=1,...,I$ be data produced by I sources, e.g. measurements produced by I sensors, and $\Theta=\{\theta_1,...,\theta_N\}$ be a set of events under consideration (in belief theory, Θ is called a frame of discernment, in possibility theory it is universe of discourse). We assume that we have a model M, which utilizes this data and prior knowledge to provide us with a degree of belief x_i in event $A \subset \Theta$: $x_i(A), i=1,...,I$. These degrees of belief take values in a real interval and are modeled within the framework of a particular uncertainty theory.

The degree of belief based on fused information is defined by operator $F(x_1,...,x_I)$ built in the framework of the theory used for belief representation (see, e.g., a classification of different fusion operators in [10]).

As it was mentioned in the introduction, in general, fusion operators $F(x_1,...,x_I)$ are symmetrical and based on the assumption that the sources are reliable. If the sources are not reliable the fusion operators have to be transformed to account for their reliability and can be represented as $F_R = F(x_1, x_I, R_1, ...R_I)$, where $R_i \in [0,1]$, $i=1,...,I$ are reliability coefficients. Reliability coefficients control influence of the respective sources on fusion results. The operator F_R is "context dependent" [10] since it depends not only on the values of x_i but also on global knowledge. R_i is close to zero if source i is unreliable and close to 1 if it is more reliable. Reliability of source i can also be a vector $\overline{R_i}=(R_{i1},...,R_{iN})$, where R_{in} is reliability of belief of source i into a particular hypothesis. In general, $R_{in} \neq R_{im}$, if $n \neq m$ since belief of the same source in one hypothesis can be more reliable than in the other. Reliability coefficients depend not only on a model selected but also on characteristics of the environment and a particular domain of the input and, therefore, we can have $R_i = R(M_i, \bar{\gamma}, \overline{\mathrm{Y}})$, where M_i is a model chosen for source i, $\bar{\gamma}$ is a vector parameters characterizing external environment of the source, e.g., meteorological conditions, or the deception ability of the observed object. Vector $\overline{Y}$ represents parameters characterizing the internal environment of the source (tuning parameters).

The problem of sources reliability is related to the problem of conflict. Indeed existence of conflict indicates existence of at least one unreliable source. At the same time, unreliable sources can agree and the absence of the conflict does not guarantee reliability of sources.

2.2 Strategies

The global knowledge about the sources, the environment, and the nature and the properties of any particular credibility model can provide different information about reliability and several situations differ by the level of knowledge about source reliability can be considered [11]:
1. It is possible to assign a numerical degree of reliability to each source.
Each value of reliability may be "relative" or "absolute" and they may or may not be linked by an equation such as $\sum_i R_i = 1$.
2. Only an order of the reliabilities of the sources is known but no precise values.
3. A subset of sources is reliable but we do not know which one.

Dealing with these situations calls for one or a combination of the two of the following strategies:
a. Strategies explicitly utilizing reliability of the sources. In that case two substrategies may be conceivable:

- It is possible to include reliability into modeling belief for each source before fusion to compensate for their different reliability and make them totally or, at least, equally reliable before fusion and then fuse transformed beliefs (separable case):

$$F_R = F(g(x_1, R_1),..., g(x_I, R_i)) . \tag{1}$$

- Each source cannot be transformed independently and reliability coefficients modify the fusion operator considered (non-separable case):

$$F_R = F(x_1,...,x_I, R_1,..., R_I) . \tag{2}$$

b. Strategies for identifying the quality of data input to fusion processes and elimination of data of poor reliability:

$$F_R = F(\overline{X}_j), \tag{3}$$

where $\overline{X}_j = (x_{i_1},...,x_{i_j})$, $i_j \le I$, and $\overline{X}_j$ is satisfied a certain reliability criterion.

The reminder of the paper will be devoted to review of the methods of building fusion operator F_R explicitly utilizing reliability coefficients.

3 Methods explicitly utilizing reliability coefficients

3.1 Bayesian methods

3.1.2 Bayesian fusion rule

In the Bayesian framework the degrees of belief are represented by *a priori*, conditional, and *a posteriori* probabilities. Usually, decisions are made on *a posteriori* probabilities $P(\theta_n \mid y_i)$, where y_i is a measurement or a feature vector coming from source i, and $x_i = P(\theta_n \mid y_i)$ represents statistics of each source to be combined (data, outputs of classifiers). Fusion is usually performed by the Bayesian rule, which under the condition of source independence is reduced to a product:

$$F_n(x_1,...,x_I)|_{y_i} = F_n(\overline{P})|_{y_i} = P(\theta_n)\prod_i^I [P(\theta_n \mid y_i)/P(\theta_n)], \forall n \quad (4)$$

This fusion operator is conjunctive and assumes total reliability of the sources.

If the sources are not totally reliable, several fusion rules within the framework of the probability theory have been proposed in the literature.

3.1.2 Weighted average methods

The majority of the weighted average methods (see, e.g., [12-15]) are based on consensus theory, which involves general procedures of combining single source probability distributions while decisions are based on Bayesian decision theory. Consensus rules are mostly used for decision fusion and combining expert subjective probabilities. Several consensus rules have been proposed. One of the most commonly used consensus rule is the linear opinion pool:

$$F_n(x_1,...,x_I,R_1,...,R_I)|_{y_i} = F_n(\overline{P},\overline{R})|_{y_i} = \sum_i P(\theta_n \mid y_i)\cdot R_i, \quad (5)$$

where R_i is reliability associated with the sources in the global membership function expressing quantitatively the goodness of each source. In this case it is easy to see that this strategy is separable.

Among other consensus rules presented in the literature are logarithmic opinion pools

$$\log F_n(\overline{P},\overline{R})|_{y_i} = \sum_i^I R_i \log P(\theta_n \mid y_i) \quad (6)$$

$$F_n(\overline{P},\overline{R})|_{y_i} = P(\theta_n)\prod_i^I [P(\theta_n \mid y_i)/P(\theta_n)]^{R_i} \quad (7)$$

Equations (4)-(7) assume that reliability R_i of each source i is the same for beliefs in each hypothesis θ_n. However, a similar formalism can be used with an assumption that the source reliabilities are different for different hypotheses. In this case classwise reliabilities R_{in} can be used in many fusion models and equations (4)-(7) can be changed in an obvious way.

Several publications address theoretical and practical issues of the performance of the system utilizing reliability coefficients in consensus based methods, so called "trained classifiers", and their comparison with simple averaging, so called "fixed classifiers" [14,15]. The theoretical model showed that "trained classifiers" could significantly outperform "fixed classifiers" only for combination of classifiers with a large difference between the error rates of the best and the worst classifier. Moreover, the differences in correlation also play an important role in the performance improvement achievable by incorporating reliability coefficients. Experiments conducted with remote sensing images and biometrics supported these theoretic results.

3.1.3 Incorporation of Contextual information

A method designed in [16,17] is based on the idea that the sensor reliability depends on the context of sensor acquisition. This method integrates contextual information into target tracking domain. The contextual analysis supervising tracking is able to detect the sensors, which are reliable and those, which are not. The developed algorithm automatically increases the importance of measurements of reliable sensors and decreases the importance of unreliable ones. Fuzzy logic is used to represent expert knowledge to describe validity of the sensors.

The method is based on the fact that, in a given context, only a subset J of a set N of all sources to be combined is valid or reliable (i.e. their belief model adequately represents reality).

$$F_n(x_1,...,x_I,R_1,...,R_I)\mid \overline{y} = \sum_{J\subseteq N} P(\theta_i \mid y_1,...,y_n,A_J)\cdot P(A_J), \quad (8)$$

where $P(A_J)$ is the probability of validity of the subset J of sensors. This probability is calculated thanks to the reliability R_i of the individual sensors. It is clear that this strategy is not separable and then falls into the second sub strategy described in 2.2.

3.2 Evidential Methods

3.2.1 Theoretical background

Evidential models encompass several models such as the Dempster-Shafer theory of evidence [18] and Transferable belief theory [19]. In the framework of the Dempster-Shafer theory information obtained from source i is represented by the basic probability assignment (bpa). Let 2^Θ be the set of all subsets of Θ, where Θ is a set of possible events (frame of discernment). A function m is called a basic probability assignment if:

$$m: 2^Q \to [0,1],\ m(\varnothing)=0,\quad \sum_{A\subseteq Q} m(A)=1. \quad (9)$$

$m(A)\in[0,1]$, where $A\subset 2^\Theta$. Basic probability assignment characterizes belief of source i that observed data belongs to subset A and $m(\Theta)$ represents our ignorance. Functions $Bel: 2^\Theta \to [0,1]$ and $Pl: 2^\Theta \to [0,1]$ are called *belief* and *plausibility* respectively are derived from $m(A)$ as

$$Bel(A) = \sum_{B\subseteq A} m(b) \quad \text{and} \quad Pl = 1 - Bel(\neg A). \quad (10)$$

$m(A)$ is a simple support function with focus $F\subseteq\Theta$ such as $m(F)=s\neq 0,\ m(\Theta)=1-s,\ m=0$ otherwise. A simple support function invests all its belief into its focal element.

Combinations of simple support functions are called separable support functions.

Fusion of independent and equally reliable basic probability assignments is performed by the Dempster rule of combination (normalized [18] or non-normalized [19]):

$$m(A) = C^{-1} \sum_{\cap A_j = A} \prod_i m_i(A_j), \qquad (10)$$

Normalization coefficient C is used in the case of the exhaustive frame of discernment and measures conflict between sources.

3.2.2 Trade- off rule

The trade-off-rule of combining basic probability assignments $m_i(A)$ (see, e.g. [20]) is similar to a weighted average rule based on probabilities:

$$m(A) = \sum_i^I R_i \cdot m_i(A) \ . \qquad (11)$$

where R_i, $i = 1,...,I$ are reliability factors.

3.2.3 Discount rules

"Discount rules" are the methods, which transform beliefs of each source represented by bpas to account for their reliability and then use these transformed beliefs in the Dempster rule of combination. This approach corresponds to the first substrategy defined in subsection 2.2, i.e., $m_i^{disc}(A) = g(m_i(A), R_i)\ \forall A \subseteq \Theta$. In general, discount rules use reliability coefficients to redistribute the degree of support between different hypotheses based on reliability of beliefs into these hypotheses. Utilizing discount rules is also one of the ways of managing conflict between sources in the case when we are sure that the frame of discernment is exhaustive [21].

There are several methods of building function g considered in the literature. One of them is defined for simple support functions m with focal element A to "discount" beliefs into this hypothesis by R_i (see, e.g. [18, 22]).

In this case for each source i we will have:

$$\begin{aligned} m_i^{disc}(A) &= g(m_i(A), R_i) = R_i m_i(A),\ \forall A \subset \Theta, \\ m_i^{disc}(\Theta) &= g(m_i(\Theta), R_i) = 1 - R_i + R_i m_i(\Theta). \end{aligned} \qquad (12)$$

The discount rule defined by (12) is used, for example, in [23], in which basic probability assignments are based on Gaussian distribution and are learned from a training set. This method has been successfully applied to diagnosis in dermatology.

The discount rule (13) represents a generalization of the discount rule (12) in which reliability coefficients may be different for different hypothesis:

$$m_i^{new}(A) = R_i(A) \cdot m_i(A)\ ,\ m^{new}(\Theta) = 1 - \sum_j R_j(A) \cdot m_j(A.)\ . \qquad (13)$$

$\forall A : m(A) \neq 0$.

In [24] this rule is used for robust target identification in uncluttered robot environment by sonar sensors. The bpas m_i with singletons θ_n $\forall n$ as foci are obtained by exploiting amplitude and "time-of-flight" differential signals, while reliability coefficients are functions of target range and azimuth estimates. In this case reliability coefficients characterizing each source are equal for all hypothesis.

In [5] the separable support functions with singletons θ_n $\forall n$ as foci built for each source as a function of distance between input data and a corresponding class representative vector are discounted by classwise reliability coefficients according to (13) and then combined. The class representative vectors are trained in an evidential reinforcement learning neural network along with the reliability coefficients.

While rules in (12) and (13) are based on the assumption that when $R_i(A)$, a reliability factor for belief of agent i in hypothesis A, is 0, the value of $m_i(A)$ contributes to ignorance, the second rule considered in [5] assumes that when $R_i(A) = 0$ the value $m_i(A)$ contributes to our belief in hypothesis $\neg A$. In this case m_i^{new} is a basic probability assignment with focal elements θ_n, $\neg\theta_n$, $\forall n$ and are obtained from m_i as follows:

$$\begin{aligned} & m_n^{new}(\theta_n) = R_{in} m_n(\theta_i)\ , \quad m_n^{new}(\neg\theta_n) = (1 - R_{in}) m_n(\theta_i)\ , \\ & m_k^{new}(\Theta) = m_k(\Theta)\ ,\ \forall k, i\ . \end{aligned} \qquad (14)$$

The feasibility of both rules has been demonstrated in a case study of recognition of natural scene images.

In a different generic model introduced in [3,25] reliability of source i ($R_{in} \in [0,1]$) is associated with a likelihood of each hypothesis $n, C_{in} \in [0,1]$, where C_{in} is based on sensor measurements and *a priori* knowledge. It is also assumed that $C_{in} \geq 0$ only for θ_n, $\neg\theta_n$, Θ, and when $C_{in} = 0$ is valid ($R_{in} = 1$), θ_n is not verified.

Two models of $g(m_i(A))$ are considered for each source i.

Model 1:
$$\begin{aligned} m_{in}(\theta_n) &= g(m_{ij}(\theta_n), R_{in}) = 0 \\ m_{in}(\neg\theta_i) &= g(m_{in}(\neg\theta_n), R_{in}) = R_{in}(1 - C_{in}) \\ m_{in}(\Theta) &= 1 - R_{in}(1 - C_{in}) \end{aligned} \qquad (15)$$

Model 2:
$$\begin{aligned} m_{in}(\theta_i) &= g(m_{in}(\theta_n), R_{in}) = R_{in} C_{in} \\ m_{in}(\neg\theta_i) &= g(m_{in}(\neg\theta_n), R_{in}) = R_{in}(1 - C_{in}) \\ m_{in}(\Theta) &= 1 - R_{in} \end{aligned} \qquad (16)$$

The basic probability assignments constructed are combined in the Dempster rule with special attention paid to the most common case, in which data originated from statistical processes. The developed model has been successfully utilized by other authors (see, e.g. [7], [26]) who successfully applied it to remote sensing, target classification and tracking, and creating a multi-model decision support system.

In general, published results support the feasibility of utilization ”discount rules” for incorporating reliability coefficients into the Dempster rule in a separable manner.

3.2.4 Modification of the fusion operator

A non-separable modification of the Dempster rule incorporating fuzzy operators applied to the reliability coefficients (17) is suggested in [20]. This rule is an illustration of the non-separable types of methods, mentioned in Section 2.2.

$$\begin{aligned} m(A) &= Xor(R_i)\cdot(\sum_{\cap A_j=A}\prod_i R_i m_i(A_j)) \\ &+And(R_i)\cdot(\sum_{\cup A_j=A}\prod_i R_i m_i(A_j)). \end{aligned} \tag{17}$$

where *Xor* and *And* are fuzzy operators. For example, they can be defined as

$$Xor(R_i)=(1-\prod_i(1-R_i))(1-\prod_i R_i),\ And(R_i)=\prod_i R_i. \tag{18}$$

Under the closed world assumption, this rule requires normalization.

Another non-separable method of incorporating reliability coefficients into fusion is proposed by the authors of [26]. This, so-called global contextual processing method (GCPM) inspired by the method developed in [16,17] (see 3.1.3), builds global probability mass used for decision making. This global probability mass represents a combination of two probability masses. The first probability mass associated with the sensor measurements is assigned to a group of several sources and obtained by the fusion of these sources. The second probability mass represents contextual information and is computed as a probability of validity of one or several sources.

3.4 Possibility and fuzzy methods

3.4.1 Basic definitions

In the framework of possibility theory (see, e.g., [2, 11,27]) information obtained from sensor i is represented by possibility distribution π. The notion of possibility distribution is equivalent to the notion of the basic probability assignment in belief theory with a different constraint:

$$\pi:\Theta\to[0,1]:\ \max_{\theta\in\Theta}\pi(\theta)=1\,. \tag{19}$$

Most of the combination rules are based on t-norms and t-conorms, the fuzzy translation of the intersection and union.

Disjunctive rule is applied when it is known for sure that at least one source of data is reliable but it is not known which one:

$$\forall\theta\in\Theta,\quad \pi^*_\cup=\cup_i\pi_i(\theta)=\max_i\pi_i(\theta)\,. \tag{20}$$

When combining equally reliable sources, a conjunctive rule is applied:

$$\forall\theta\in\Theta,\quad \pi^*_\cap=\cap_i\pi_i(\theta)=\inf_i\pi_i(\theta)\,. \tag{21}$$

Possibilistic approach offers several fusion rules, among which are the ones explicitly taking into account available knowledge of the value of reliability coefficients. A number of such methods are reviewed in [2, 11,20, 27].

3.4.2. Trade-off rules

Trade-off rules are similar to the trade-off rule used in evidence and probabilistic methods [2]:

$$\forall\theta\in\Theta,\quad \pi_p(\theta)=\sum_i^I R_i\cdot\pi_i(\theta)\,. \tag{22}$$

As previously, both relative and absolute reliability coefficients $R_i > 0$ can be considered. The operator in (22) has no links to logical ones defined in (20) and (21).

In [28] a trade-off operator is combined with logical ones in the so-called flexible aggregation rule:

$$\forall\theta\in\Theta,\quad \pi_{\cup p}(\theta)=\sigma\sum_i^I R_i\cdot\pi_i(\theta)+(1-\sigma)\pi_\cup(\theta), \tag{23}$$

where $\sigma\in[0,1]$ is learned form data.

3.4.3 Discount rules

Reliability of sources can also be taken into account by discount rules, which modify the possibility distribution according to their level of reliability before fusion [29]:

$$\pi'_i=\max(\pi,1-R_i)\,, \tag{24}$$

where R_i is the degree of certainty that the source is reliable. As it follows from (24), if $R_i=1$ (source *i* is fully reliable) then $\pi'_i=\pi$, when $R_i=0$ (source is absolutely unreliable) then $\pi'_i=1$, which means total ignorance.

A discounting method similar to one used in the evidence framework is proposed in [30]:

$$\pi'_i=R_i*\pi+1-R_i\,, \tag{25}$$

where operator * is t-norm (disjunction).

After sources are discounted according to their reliability levels as described above, they are considered absolutely reliable and then fused by the conjunctive rule. The drawback of these rules is that when $R_i=0$ then the support of discounted distribution becomes the whole universe.

Two non-separable methods utilizing "absolute" reliability levels are introduced in [2]. The first one is defined by equation (26):

$$\forall \theta \in \Theta, \quad \pi_0(\theta) = Xor(R_i)\max_i(R_i\pi_i(\theta)) + And(R_i)\min_i(R_i\pi_i(\theta)), \tag{26}$$

where *Xor* and *And* are equivalents of the logical operators. They can be defined by the * operator, e.g., when * is a product they are the same as in (18).

This rule is not normalized and, in the case in which the assumption of a closed world is made, requires normalization. This rule has the same drawback as rules in (24), (25). To overcome this drawback, a different rule is proposed:

$$\forall \theta \in \Theta, \quad \pi_0(\theta) = Xor(R_i)\max_i(R_i\pi_i(\theta)) + And(R_i)\min_i(R_i\pi_i(\theta)) + Nor(R_i), \tag{27}$$

The rule in (27) requires the result to be complete ignorance if all sources are absolutely unreliable

The methods utilizing possibilistic and fuzzy approaches described above form a foundation for building fusion processes applied in many fields such as medical image processing [10], remote sensing [31], face recognition [32], recognition of crises [33].

4 Reliability coefficients

One of the major problems of incorporating reliability into fusion is the problem of obtaining reliability coefficients. The value of reliability coefficients may be provided by external sources, modeled by utilizing contextual information (see, e.g. [16,17,26]), learned by using training data, as e.g., in a neural network (see, e.g., [5,34,35]), or constructed as a function of agreement between different sources or sources and fusion results [2], [36]. Discussion on these methods in the literature is presented below.

4.1 Methods utilizing domain knowledge and contextual information

In [16,17] context is modeled by a set of parameters influencing reliability of each sensor and expert knowledge is used to represent validity of the sensor domain as a fuzzy membership function of the context. Then reliability coefficients are modeled as the probability of fuzzy events.

Two other methods of defining sensor reliability based on contextual information are introduced in [26]. Both methods utilize subjective contextual information modeled by the theory of fuzzy events and used in connection with probability theory. In one (LCCM method), reliability of each source is defined by associating of each sensor and each hypothesis to the context and computed as a Bayesian probability mass on the frame of discernment defined by validity domain of each source. Then obtained reliability values are used in a discount rule introduced in [26]. In another method, GCPM, inspired by the method suggested in [16,17], reliability of one or a combination of several sensors is computed as the probability of conjunction of the fuzzy subsets corresponding to each source for each contextual variable. This probability of validity is further used for the construction of reliability of one or several associations of sources and hypothesis.

In [37] expert knowledge is used to represent reliability by a possibility distribution defined on the sensor domain. The computed reliability coefficients are then used in a production system to determine the sources of satisfactory reliability to be used in combination.

The methods utilizing contextual information either in the form of *a priori* distributions or represented by validity domain for modeling reliability are very successful however this information not always available.

4.2 Obtaining reliability coefficients from training data

A general approach to learning reliability coefficients from training data consists in integrating reliability assessment into the fusion process and explicitly training fusion rules. Reliability coefficients in such methods are computed by minimizing the distance between a vector of beliefs obtained as the result of fusion within the framework of uncertainty theory considered and a target vector from a training set (see, e.g., [5, 34, 35]).

Another method of defining reliability is based on separability of different hypotheses: a source is called reliable if separability is high and not reliable if separability is low [23,38]. Reliability is measured by average or hypothesis specific distance (e.g., Bhattacharyya distance or Hellinder's distance) between probability distributions estimated from a training set.

The methods of learning reliability factors require a training set and the advantages of incorporating reliability into fusion processes may be diminished by a small number of training patterns available. However this type of methods can be very useful for establishing relative reliability of legacy classifiers.

4.3 Reliability based on consensus

Another approach to modeling source reliability employs a degree of consensus among various sources or a degree of consensus among sources and fusion results.

One of such methods designed for target tracking [36] adaptively computes a deviation between measurements of each sensor and the fusion result and uses this deviation measure as a degree of reliability of this sensor.

A different consensus based method utilizes the notion of inner trust introduced in [2]. Evaluation of inner trust is performed in two steps. At the first step a pairwise likeliness of the sources is computed and then the inner trust is defined in such way that a source is considered absolutely reliable if and only if there is no contradiction with other sources while a source in absolute contradiction have a very small reliability.

Consensus based methods has the advantage of not using any supplementary information for modeling reliability. However, this method is not always good since if sources are unreliable they may be conflicting or not. One of the ways to improve the inner trust is to complement it with any external information, which can become available [2].

4.4 Reliability of expert judgments

Reliability weights in the consensus rules for combining experts' subjective probabilities are discussed e.g. in [39,40]. The author of [39] introduced two measures of performance: calibration and information scores. The information score is defined by degree to which an expert's distribution is concentrated relative to some background measure (usually of uniform or loguniform distribution over an intrinsic range for each variable). Calibration of expert *e*, *C(e)*, is the statistical likelihood that an expert's quantile assessment corresponds to a set of experimental results.

This approach inspired development of the methodology introduced in [39], in which expert opinions are modeled by possibility distributions, which represent expert judgments more naturally than probabilities. Reliability of an expert in [40] is measured by membership grades (calibration) and by fuzzy cardinality indexes (level of precision).

5. Reliability of fusion results

A very important question related to designing a fusion system is a question of reliability of the fusion results. Although all the publications report improved fusion systems performance as the result of incorporating reliability into fusion processes, the reliability of the results obtained with such fusion processes has seldom been investigated. It is usually assumed that incorporation of source reliability makes fusion result perfectly reliable and the number of publications addressing this problem is very limited.

The authors of [2,20] are studying reliability of the possibility based fusion operator (see 3.4.2) and propose to measure reliability of the fusion result as a combination of its "direct reliability" and an index of its quality. "Direct reliability" is modeled as a trade off between a reinforcement function of reliability of the sources and a function of the number of sources. The quality index measures internal contradiction of the result and depends on its the shape of the result, namely on the extend to which a resulting possibility distribution contains several different modes and the extend to which they overlap.

The authors of [37] assume that reliability of the fusion result obtained by propagating sensor measurements through the layers of a recurrent neural network can be assessed by propagating sensor reliability the same way. Thus, the reliability of the result is computed as a function of reliability of the sensors and the architecture of the neural network used.

In [40] reliability assessment of fusion results is conducted by treating the aggregated result as a "virtual expert", which allows for comparing different pooling methods considered in the paper.

6. Conclusion

This paper presents a discussion of definitions and issues related to incorporation of reliability of sources into information fusion. Review of publications addressing theoretical and practical issues of designing such methods within the framework of probability, evidence, and possibility theories is presented. Incorporation of reliability into fusion processes gives "richer behavior" to the fusion system while producing many theoretical and practical problems not very often addressed in the data fusion literature. Among these problems are the problem of estimation of reliability of sources and their temporal analysis; the problem of interrelationship between reliability of information sources, their number, and the reliability of fusion results; the problem of incorporating reliability into fusion of heterogeneous information.

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