Reliability estimation based on conflict for evidential database enrichment

Mouna Chebbah
LARODEC
ISG Tunis - Tunisia
Email: Mouna.Chebbah@gnet.tn

Boutheina Ben Yaghlane
LARODEC
IHEC Carthage - Tunisia
Email: boutheina.yaghlane@ihec.rnu.tn

Arnaud Martin
E^3I^2, EA3876
ENSIETA - Brest
Email: Arnaud.Martin@ensieta.fr

***Abstract*—The theory of belief functions is used for representing uncertain information and also for combining several sources' opinions. The conflict appearing in the combination can be computed from a distance measure in the purpose of estimating the relative reliability of each source. This conflict can be managed before the combination step by taking into account the reliabilities of the sources and discounting the related information. This method needs knowledge about the sources' degree of reliability, which can be estimated from the related belief function. In this paper, we propose a generalization method for sources' reliability estimation taking into account all its belief functions stored in an evidential database and also insuring the same level of reliability for all these belief functions by discounting the related plausibility functions. This method is evaluated on real radar data and supplied good results in terms of sources' reliability improvement.**

Keywords: Conflict measure, discounting, evidential database, classification, plausibility function.

I. Introduction

Relational databases are used to store high quantity of structured data in tables where each row in the table holds the same sort of information. These data can come with different levels of certainty. Therefore, when a database contains uncertain data and the uncertainty is represented by the theory of evidence, it is named *evidential database* as presented in [1] and [8]. Combining evidential data reduces the quantity of stored information, eliminates redundant information and helps the user when decision making. Furthermore, this combination helps the user to take into account several sources' opinions.

The theory of belief functions used in evidential databases is a strong tool for combination. Indeed, this theory proposes a large number of combination rules to combine several evidential information although a problem may appear if their sources are completely or even partially in conflict.

The conflict coming from the combination of conflicting evidential information incited the apparition of several methods intended to solve it. Some of these methods propose to solve the conflict when combining, like in [6], [12], [15] and [18], these combination rules hide the conflict regardless of its causes. Therefore, the conflict does not appear in the combined information because combination rules redistribute it with different manners. Other methods, like in [11], consider that the main reason of the conflict apparition is the relative unreliability of at least one of the sources. Therefore, conflict resolving can be insured by discounting evidential information before combining proportionally to the source's degree of reliability but this method requires a preliminary knowledge of this degree of reliability.

In this paper, we propose to estimate source's reliability degree taking into account all its evidential information which are available in an evidential database. Indeed, all evidential information available in an evidential database can serve to estimate the reliability of this source. This reliability rate is used to discount the related plausibility functions supplied by the corresponding source in order to prevent any conflict apparition in the combination step.

Furthermore, we propose also an enrichment of the evidential databases by adding sources' reliabilities before and after discounting and also combination reliabilities. These two latter information will be used by the user in the decision process and the first one is useful for evidential database update to discount new plausibility functions corresponding to new bbas.

The rest of this paper is organized as follows: in Section II, we recall some basic concepts of the theory of belief functions. Then, in Section III, we introduce evidential databases used for storing evidential information supplied by a source. After this, we propose in Section IV a generalized method for reliability estimation taking into account all source's evidential information stored in its evidential database. Finally, in Section V, the proposed method is used to combine three classifiers' evidential information for target recognition with real radar data.

II. Belief function theory

A. Formalism

The theory of belief functions, also called theory of Dempster-Shafer or theory of evidence, was first introduced by Dempster in [3], [4] and was mathematically formalized by Shafer [13]. The theory of belief functions is used for representing imperfect (uncertain, imprecise and/or incomplete) information. We present here some basic concepts of this theory.

Let $\Omega = \{\omega_1, \omega_2, \ldots, \omega_n\}$ be a finite non empty set of all elementary and mutually exclusive hypotheses related to a given problem. Ω represents the *frame of discernment* of the studied problem.

A *basic belief assignment (bba)* is defined on the set of all subsets of Ω, namely *power set* and noted 2^{Ω}. It affects a real value from $[0,1]$ to every subset of 2^{Ω} reflecting source's amount of belief on this subset. A bba m is the function:

$$m : 2^{\Omega} \mapsto [0,1] \quad (1)$$

such that:

$$m(\emptyset) = 0 \quad (2)$$

$$\sum_{X \subseteq \Omega} m(X) = 1 \quad (3)$$

The *belief function* (bel) is computed from a bba m. $bel(A)$ is the minimal belief affected to A justified by available information on B ($B \subseteq A$):

$$\begin{aligned} bel : 2^{\Omega} &\rightarrow [0,1] \\ A &\mapsto \sum_{B \subseteq A, B \neq \emptyset} m(B) \end{aligned} \quad (4)$$

The *plausibility function* (pl) is also derived from a bba m. $pl(A)$ is the maximal belief affected to A justified by information on B which are not contradictory with A ($A \cap B \neq \emptyset$):

$$\begin{aligned} pl : 2^{\Omega} &\rightarrow [0,1] \\ A &\mapsto \sum_{A \cap B \neq \emptyset} m(B) \end{aligned} \quad (5)$$

B. Combination rules

Combination rules are used to combine several belief functions provided by different sources in the purpose to have only one resuming all the others. There is a great number of combination rules [16], whereas we present in table I only those used in the last section of this paper.

For Dempster's rule of combination [3], Yager's rule of combination [18] and Dubois and Prade's rule of combination [6], the frame of discernment Ω is exhaustive implying that all possible hypotheses are enumerated on Ω and a null mass is affected to the empty set. These rules are *normalized* and work under the *closed world assumption*.

The conjunctive rule of combination proposed by Smets in [15] is the only rule which works under the *open world assumption* where a non null mass can be affected to the empty set representing the degree of belief that the attribute's real value is not enumerated on Ω.

Most of presented rules in table I are based on the conjunctive rule of combination but they are different in the manner of conflict redistribution. Murphy's combination rule, presented in [12], is here the only presented rule which is not based on the conjunctive rule of combination and conflict does not appear if the combined bbas are normalized.

C. Discounting

The main reason of the conflict apparition when combining two bbas is the relative reliability of their sources. When at least one of sources is unreliable ($m(\emptyset) > 0$), $m(\emptyset)$ is interpreted as the amount of conflict [3]. This conflict can be managed by the used rule itself, but the better solution is to reduce or eliminate it from the beginning (before combination) using the discounting operator. Discounting allows conflict solving independently of the used combination rule. Discounting can be done sequentially as described in [14]. If sources' reliability rates α_i are known or can be quantified, discounting a bba m^{Ω} is defined as follows:

$$\begin{cases} m^{\alpha_i}(A) = \alpha_i \times m^{\Omega}(A) & \forall A \subset \Omega \\ m^{\alpha_i}(\Omega) = 1 - \alpha_i) + \alpha_i \times m^{\Omega}(\Omega) \end{cases} \quad (6)$$

where α_i is the reliability degree of the i^{th} source.

This operator weakens or strengthens bbas, mass by mass, proportionally to sources' reliabilities. Therefore, this operator does not affect focal elements but does change only masses. That is why, we propose in this paper to discount plausibility function rather than bba.

Plausibility discounting proposed in [19] consists on, first, computing plausibility function from bba using equation (5). Second, discounting plausibility function using source's reliability degree α:

$$pl'(A) = [pl(A)]^{\alpha} \quad \forall A \subseteq \Omega \text{ and } A \neq \emptyset \quad (7)$$

and finally, computing bba from discounted plausibility function:

$$\begin{cases} m'^{\Omega}(A) = \sum_{B \subseteq A} (-1)^{|A|-|B|+1} pl'(\bar{B}) & \forall A \subseteq \Omega \\ m'^{\Omega}(\emptyset) = 1 - pl'(\Omega) \end{cases} \quad (8)$$

To use plausibility discounting, sources' degree of reliability have to be known, estimated or learned.

III. Evidential Database

An *evidential database* (*EDB*), also called *DS database*, is a database containing certain and/or uncertain data, uncertainty is expressed using the theory of belief functions as presented in [1] and [8].

An evidential database is a database having X records and Y attributes such that every attribute y ($1 \leq y \leq Y$) has a domain D_y containing all its possible values. D_y is the *frame of discernment* of the y^{th} attribute [8].

An EDB must have at least one *evidential attribute*, values of this attribute are uncertain and are represented with different bbas as defined in [1]. An *evidential value* V_{xy} for the x^{th} record and the y^{th} attribute is a bba such that:

$$\begin{aligned} & m_{xy} : 2^{D_y} \rightarrow [0,1] \text{ with:} \\ & m_{xy}(\emptyset) = 0 \text{ and } \sum_{A \subseteq D_y} m_{xy}(A) = 1 \end{aligned} \quad (9)$$

An example of an evidential database is described in table II, this evidential database contains targets detected by several sensors. The attribute target is the only evidential attribute in this evidential database, its frame of discernment is $\Omega_{target} = \{Plane\ P,\ Helicopter\ H,\ Missile\ M\}$.

This evidential database stores data of different levels of certainty. It stores:

- Probabilistic data where all focal elements are singletons like the value of the attribute target for the first record of table II.

Table I
CONFLICT REDISTRIBUTION METHODS OF COMBINATION RULES

Combination rule	Characteristic of Ω	Conflict redistribution
Conjunctive rule of combination	Not exhaustive (open world assumption)	Conflict is not redistributed
Dempster's rule of combination	Exhaustive	The conflict is redistributed proportionally on the subsets of Ω
Yager's rule of combination	Exhaustive	$m(\emptyset)$ is affected to Ω
Dubois and Prade's rule of combination	Exhaustive	Masses resulting of conflicting focal elements combination are affected to these focal elements
Murphy's rule of combination	Exhaustive/Not exhaustive	If combined bbas are normalized then conflict does not appear else the conflict is not redistributed

- Possibilistic data where all focal elements are nested and the possibility function corresponds to the plausibility function like target's value for the second record of table II.
- Missing data where no information is available therefore the unit is attributed to Ω like the value of the attribute target for the third record from table II.
- Evidential data where data is not probabilistic nor possibilistic like the value of the attribute target for the fourth record in table II.
- Certain data where the attribute's value is known with certainty like the value of the attribute target for the last record.

Table II
EXAMPLE OF AN EDB

Sensor	Time	Target
S_1	t_1	$P(0.3)$ $H(0.7)$
S_2	t_2	$P(0.2)$ $P \cup H(0.6)$ $\Omega(0.2)$
S_1	t_2	$\Omega(1)$
S_2	t_3	$P(0.4)$ $\Omega(0.6)$
S_3	t_3	P

Evidential databases are used in different areas such that classification where they stock bbas supplied by different classifiers such as in [8].

IV. RELIABILITY ESTIMATION

An evidential database is used to stock different bbas supplied by a source, therefore the number of evidential databases is dependent on the number of sources. Having s sources implies the existence of s evidential databases such that every EDB belongs to a source. Integrating these s evidential databases reduces the quantity of information to be stocked and also helps the user in decision making, thus the latter have to take into account only one EDB which resumes s ones.

When integrating evidential values from several EDBs, a conflict may appear. In this paper, we propose to discount plausibility functions computed from bbas (evidential values) to be integrated in order to prevent the conflict which may appear when combining. We propose also to indicate sources' and combinations' degrees of reliability for the user to help him in decision process by saving these information in the EDB.

Discounting plausibility functions of bbas supplied by a source needs an *a priori* knowledge about source's degree of reliability. Although source's degree of reliability is not always available, it can be estimated from supplied bbas.

A. Conflict estimation

Martin et al. proposed in [11] a conflict estimation method based on distance measure, the degree of conflict between two sources is related to the distance between their corresponding bbas. Jousselme distance [9] is used in this paper because it takes into account specificities of belief functions owing to the matrix D which is defined on 2^Ω contrary to other distances [7] which can be also used but they are not defined on 2^Ω.

$$d(m_1, m_2) = \sqrt{\frac{1}{2}(m_1 - m_2)^t \underline{\underline{D}}(m_1 - m_2)} \qquad (10)$$

with :

$$D(A, B) = \begin{cases} 1 & \text{if A=B=}\emptyset \\ \frac{|A \cap B|}{|A \cup B|} & \forall A, B \in 2^\Omega \end{cases} \qquad (11)$$

The degree of conflict between two sources (S_1 and S_2) is the distance between their corresponding bbas, respectively m_1 and m_2.

$$\text{Conf}(S_1, S_2) = d(m_1, m_2) \qquad (12)$$

Equation (12) is applied with only two sources. When the number of sources exceeds two, the conflict measure based on a distance measure may be computed in two different ways depending on the type of used distance:

- **Distance type 1:** is the mean of distances between a bba m and other bbas without using a combination rule.
  For s sources, the distance between a bba m_j supplied by the source S_j and the bba m_M representing all the $s-1$ other bbas except m_j is computed as follows:
  $$d(m_j, m_M) = \frac{1}{s-1} \times \sum_{i=1, i \neq j}^{s-1} d(m_j, m_i) \qquad (13)$$
- **Distance type 2:** is the distance between a bba m_j supplied by the source S_j and the combined bba of all other bbas except m_j. This method needs a use of a combination rule to combine the $s-1$ bbas. Combination rules previously described may be used in this context as well as those not quoted.
  For s sources, the conflict of the source S_j with all the other sources corresponds to the distance between m_j,

the bba supplied by this source, and m_M representing the combined bba of the $s-1$ sources.

B. Source's reliability estimation

Once source's degree of conflict is computed, the *relative reliability* of this source can be also computed. Martin et al. in [11] proposed a method for estimating the relative reliability α_j of a source S_j based on the conflict measure as follows:

$$\alpha_j = (1 - \text{Conf}(S_j, s)^\lambda)^{\frac{1}{\lambda}} \tag{14}$$

with λ is a real not null.

The coefficient α_j is called relative reliability because it takes into account only one bba. In practice, an evidential database stocks a greet number of bbas supplied by the same source. Source's reliability has to take into account all bbas supplied by this source thus it is computed from all its relative reliabilities.

For example, let s be the number of EDBs corresponding to s sources. Every EDB has X records and Y attributes, thus each source from s ones has $X \times Y$ relative reliabilities.

In this paper, we propose to use the mean of $X \times Y$ relative reliabilities as the *global reliability* of the source. The mean of relative reliabilities is chosen because a source keeps, in general, the same level of reliability. Although a source may sometimes make a mistake and be reliable or unreliable while it is not in general, it keeps in average the same level of reliability.

Choosing the mean avoid using extreme values like minimum and maximum for discounting. Indeed, discounting using the minimal reliability reduces bbas to the total ignorance and discounting using the maximal reliability keeps bbas unchanged, but discounting using the mean improves sources' reliability and keeps bbas' integrity.

Therefore, the global reliability a_j^g of a source S_j is the mean of its X relative reliabilities α_{xj}:

$$\alpha_j^g = \frac{1}{X} \sum_{x=1}^{X} (\alpha_{xj}) \tag{15}$$

C. Combination's reliability estimation

Let s be the number of sources supplying, every one, a bba. For each bba, a relative reliability α_j is computed by estimating the conflict between its source S_j $(1 \leq j \leq s)$ and all the others using a distance measure.

A reliability degree can be affected to the bba result of combining these s bbas in order to indicate to the user how much the combined information used for decision making is reliable.

Combination's reliability α_c is the mean of s combined bbas' relative reliabilities α_s.

$$\alpha_c = \frac{1}{s} \times \sum_{j=1}^{s} (\alpha_j) \tag{16}$$

The value α_c is useful only for the user who may use it to take into account combined bba's reliability degree in decision process.

Equations (15) and (16) are different: the first one computes source's reliability which is the mean of all its relative reliabilities and the second one computes combination's reliability which is the mean of relative reliabilities of combined bbas.

V. Illustrations

To test the method described above, we considered a database containing radar data. The real data were obtained in the anechoic chamber of ENSIETA (Brest, France) using a target radar sensor with different angular positions. The acquisition process is described in [10] and a model of database used for storing corresponding frequency data is proposed in [17]. Each database contains 250 frequencies obtained on angular position about 60° and using a frequency band of 6 GHZ. We considered five radar target (namely Mirage, F14, Rafale, Tornado, Harrier) and three classifiers considered as sources. These classifiers which are: fuzzy K-nearest neighbour, belief K-nearest neighbour [5] and neural network are used to analyze and classify frequencies data in order to produce 250 bbas. These 250 bbas (for each source) are stored in three tables which we use to test our method.

Our purpose is to integrate the three tables by combining the 250 bbas of each source in order to have only one table. Combining three tables in one table will help user when decision making.

We also aim to ensure the same level of reliability for all bbas provided by the same source and this reliability level is the source's one. When all source's bbas have the same level, cases when source is wrong are discounted and user may use all bbas without carrying about mistakes because they are corrected. To be sure that all bbas provided by the same source have the same level, we have to reduce the variance of relative reliabilities. Also, enriching databases by adding extra information about sources' initial reliability degree (source's reliability degree before discounting) to be used for maintaining databases if new data are added and have to be integrated. Adding combinations' degree of reliability will inform users about the pertinence of combined bbas especially that the user will use the integrated database rather than the initial ones separately.

Our method can be divided into two steps:

- **Step 1: Sources' reliability estimation.** We have three tables containing every one 250 bbas, a conflict measure is attributed to every bba using distance type 1 and distance type 2 with combination rules described in Section II-B. Conflict estimation method is described in Section IV-A. These conflict measures are used to estimate the relative reliability of each bba using equation (14).

  Therefore, we obtained 250 relative reliabilities for each source (fuzzy K-nearest neighbour, belief K-nearest neighbour and neural network). Table III contains the minimum, maximum and mean of relative reliabilities for each source with distance type 1 for conflict estimation and $\lambda = 1/2$.

  Discounting with the minimal reliabilities which are very small (0.073, 0.029 and 0.09) will reduce bbas to the

Table III
MINIMUM, MAXIMUM AND MEAN OF RELATIVE RELIABILITIES

Source	Max	Min	Mean
Fuzzy K-nearest neighbour	0.741	0.073	0.313
Belief K-nearest neighbour	0.676	0.029	0.28
Neural network	0.719	0.09	0.205

case of total ignorance, discounting with the maximal reliabilities which are high (0.741, 0.676 and 0.719) does not really affect bbas, and finally discounting with the mean of relative reliabilities reduces the conflict and also keeps the structure of bbas unchanged.

Therefore, we choose the mean of these 250 relative reliabilities as source's global reliability. In table IV, an example of initial sources' reliabilities is presented for different values of λ (parameter used to estimate reliability measure from conflict one) and using distance type 1 for conflict estimation. For simplicity of calculation, we have computed 250 conflict values for each source then we used the mean to estimate source's reliability. This method reduces the number of use of equation (14), thus it is used only once rather than 250 times.

Table IV
INITIAL RELIABILITIES

Sources\ λ	0.5	1	2
K-NNF	0.3108	0.8042	0.9806
K-NNB	0.2782	0.7767	0.9747
NNET	0.2034	0.6986	0.953497792

- **Step 2: Plausibility discounting.** In this step, plausibility discounting is proceeded as described in Section II-C producing 250 discounted bbas. Reliabilities are re-estimated after discounting (same procedure as step 1). Figure 1 describes reliabilities' improvement rates and relative reliabilities' variances decrease rates for different values of λ for the neural network.

  The choice of λ is done according to reliabilities' improvement rates and relative reliabilities' variances decrease rates. The greater are these two measures more we improve sources' reliabilities and ensure the same level of bbas' relative reliabilities.

  Reliability increases with the growth of lambda, therefore λ have to be chosen as greater as possible to discount bbas at minimum with getting better results. For example, $\lambda = 0.25$ is the best value of λ for neural networks (from figure 1) but $\lambda = 0.2$ is the best value to use for reliability estimation for fuzzy K-nearest neighbour and belief K-nearest neighbour. We summarize results of tests in the table V. This method improves sources' reliabilities and insures the same level of relative reliabilities because the variances after discounting are almost equal to zero.

The method presented in [2] estimates source's reliability as described in section IV and discounts bbas before combining but in this paper we discount plausibility functions rather than bbas. Table VI presents results in terms of reliabilities improvement rates for both methods.

Table V
RESULTS' TESTS

Sources	Chosen λ	Initial reliability	Initial variance	Reliability after discounting
K-NNF	0.2	0.0017	0.0137	0.1555
K-NNB	0.2	0.0012	0.0177	0.1352
NNET	0.25	0.0004	0.0339	0.1273

Table VI
COMPARISON OF PLAUSIBILITY DISCOUNTING AND BBA DISCOUNTING

Source	Type	Reliability improvement	
		bba discounting	pl discounting
K-NNF	Type1	0.687	0.9893
	Type2 (DS)	0.1667	0.8361
	Type2 (Mean)	0.4466	0.9748
K-NNB	Type1	0.7444	0.9914
	Type2 (DS)	0.2475	0.6925
	Type2 (Mean)	0.7892	0.9915
NNET	Type1	0.7998	0.9591
	Type2 (DS)	0.1578	0.5661
	Type2 (Mean)	0.7558	0.9438

Plausibility discounting improves reliabilities better than bba discounting and both of methods insure the same level of relative reliabilities for all bbas after discounting. Variances of relative reliabilities after discounting are very small (almost 0) for both methods.

VI. CONCLUSION

In this paper, we proposed to estimate the conflict degree of a source on the bases of all its bbas. This conflict degree is evaluated for each source against all the others for each bba supplied by this source. Based on these conflict degrees, we compute the relative reliability for each bba according to each source. Sources' reliabilities are the mean of all its relative reliabilities; they are used to discount plausibility functions before combination. Our method based on reliability estimation and plausibility functions discounting is evaluated on real radar data target recognition. It provides good results in terms of reliability improvement and also corrects bbas where the source makes mistake by ensuring the same level of relative reliabilities for all bbas supplied by the same source. In our method, we proposed also an enrichment of the evidential databases by adding source's reliabilities before and after discounting and also combination reliabilities. For further works, we propose to define a distance measure which takes into account specificities of plausibility functions in the purpose to estimate the conflict degree of a source on the bases of all its plausibility functions rather than bbas.

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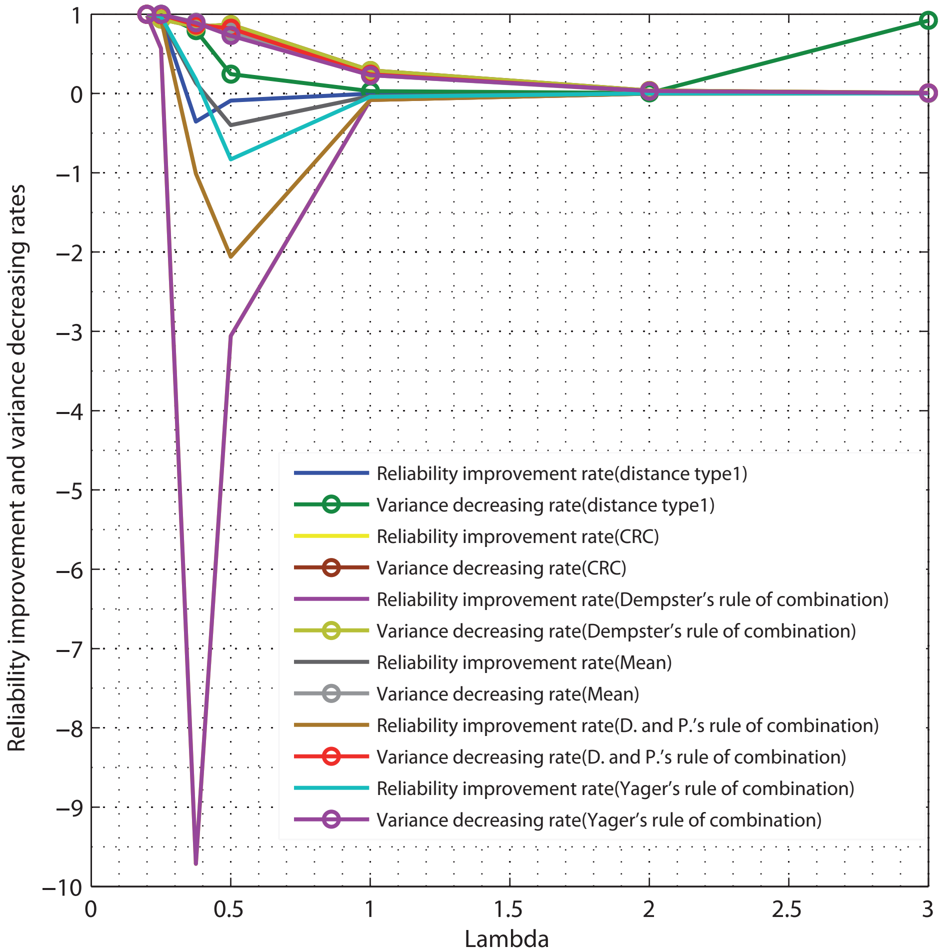

Figure 1. Reliabilities improvement and variances decrease rates for NNET

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