Reliability estimation with Extrinsic and Intrinsic measure in belief function theory

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Abstract—Belief function theory provides a robust framework for uncertain information modeling. It also offers several fusion tools in order to profit from multi-source context. Nevertheless, fusion is a sensible task where conflictual information may appear especially when sources are unreliable. In belief function theory, a classical approach would estimate the source's reliability before any discounting operation. Existing solutions for source's reliability estimation, are based on the assumption that distance is the only factor for conflictual situations. Indeed, integrating only distance measures to estimate source's reliability is not sufficient where source's confusion may also be considered as conflict origin. In this paper, we tackle reliability estimation and we introduce a new discounting operator that considers those two possible conflict origins. The proposed approach is applied on benchmark data for classification purpose.

Index Terms—Belief function theory, Discounting, Intrinsic measure, Extrinsic measure, Distance classifier.

I. INTRODUCTION

Since its introduction by Dempster [3] and its formalization by Shafer [15], the belief function theory has shown to be as one of the most adequate formalism in information fusion domain. It not only allows modeling mathematically uncertainty and imprecision information but it also integrates many combination tools allowing source fusion [19]. Thanks to the numerous combination tools it integrates, the extraction of the pertinent information from a large set of source became an easy task.

Despite its obvious advantages, it presents some drawbacks encountered when we fuse conflictual (contradictory) information sources. In 1965, Zadeh [21] highlighted the counterintuitive behavior of the first proposed combination rule [3] with an example proving the difficulty of contradictory sources combination. As a result, fusing contradictory sources has become a research field. A wealthy number of works put the focus on in proposing solutions to handle conflict and two types of approaches can be distinguished: (*i*) Conflict redistribution based approaches; (*ii*) Discounting unreliable source based approaches.

The conflict redistribution family consists in combining sources and the registered conflict is directed to a hypothesis depending on the adopted heuristic. This type of approaches was largely addressed in the dedicated literature e.g., [19]. The discounting family approach aims at treating studied sources before combination. In fact, those approaches are based on the idea that conflict is inducted and generated by the unreliability of at least one source. The unreliable sources are discounted by a coefficient affecting its consideration during the combination phase. Many works have been carried out in this domain finding those discounting factors [12], [8], [11]. Comparatively to the redistribution family, the discounting approaches are less explored by researches because of difficulty of measuring source reliability. Nevertheless, some interesting works have been proposed lately based on source's distance measure and providing some interesting results. Indeed all those works [9], [2], [16] were based on the assumption that more a source is distant to the others (source in contradiction with other ones), the more unreliable is.

Shafer [15] highlighted that, the resulting conflict may not only come from the source's contradiction during the combination phase. Indeed, the confusion rate of a source may generate a conflict. This assumption means that the more the source is less informative, the higher the conflict is. To the best of our knowledge, rare are the discounting based approaches that addressed conflict taking those two conflict origins into consideration.

In this paper, we consider two possible factors that should be taken into consideration for conflict management. The *Intrinsic conflict* caused by the unreliability of a source to determine certain classes. The second considered conflict origin is the *Extrinsic conflict* which indicates to what extent the obtained sources are in contradiction. In this work, we aim to elaborate a reliability measure based on the Extrinsic and Intrinsic conflict of a source. This measure will be integrated into classifier based on the belief function formalism, which is able to detect unreliable sources and discount them.

This paper is organized as follows: the second section briefly reminds the basics of the belief function theory. In the third section, we discuss different measures introduced to estimate source reliability. We scrutinize, several works that used those measures in order to elaborate a discounting conflict management approach. In section IV, we introduce the Generic Discounting Factor discounting operator allowing belief function reliability estimation regarding its two sided conflict measures. Finally, we introduce the GDF classifier based on a distance belief function estimation. This classifier

is experimented on several benchmarks comparatively to some pioneer approaches and we sketch issues of future work.

II. BELIEF FUNCTION THEORY: THEORETICAL BACKGROUND

The belief function (or evidence) theory was introduced by Dempster [3] in order to represent some imprecise probabilities with upper and lower probabilities. Then, it was mathematically formalized by Shafer [15]. The belief function theory was mainly used for representing imperfect (uncertain, imprecise and/or incomplete) information. We present in the following the key concepts of this theory.

A. Frame of discernment

The frame of discernment is the set of possible answers for a treated problem and is generally denoted θ. It is composed of exhaustive and exclusive hypotheses,i.e,

$$\theta = \{H_1, H_2, ..., H_N\}.$$

From the frame of discernment θ, we deduce the set 2^θ containing all the 2^N subsets A of θ:

$$2^\theta = \{A, A \subseteq \theta\} = \{H_1, H_2, ..., H_N, H_1 \cup H_2, ..., \theta\}.$$

B. Basic Belief Assignment

A basic belief assignment (BBA) m is the mapping from elements of the power set 2^θ into [0, 1] such that:

$$m : 2^\theta \longrightarrow [0, 1]$$

such that:

$$\begin{cases} \sum_{A \subseteq \theta} m(A) = 1 \\ m(\emptyset) = 0. \end{cases} \tag{1}$$

Each subset X of 2^θ fulfilling $m(X) > 0$ is called a *focal element*. Constraining $m(\emptyset) = 0$ is the normalized form of a BBA and this corresponds to a closed-world assumption [18] whereas allowing $m(\emptyset) > 0$ corresponds to an open world assumption [17].

From a BBA, another function can be defined. The plausibility, denoted $Pl(A)$, is a measure of the maximum potential support that could be given to A, if further evidence becomes available and defined by:

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B). \tag{2}$$

The pignistic probability, denoted $BetP$, was proposed by Smets and Kennes [17] within the Transferable Belief Model (TBM) approach. The pignistic transformation is generally considered as a good basis for a decision rule where it considers even the composite hypothesis in its treatment, Formally:

$$BetP(H_n) = \sum_{A \subseteq \theta} \frac{|H_n \cap A|}{|A|} \times m(A) \qquad \forall H_n \in \theta. \tag{3}$$

C. Combination operators

The belief function offers many advantages. One of its proposed asset is the information fusion allowing extracting the more veracious proposition from a multi-source context. This benefit is granted by the combination rules. Several operators were defined such as the conjunctive rule allowing fusion without any normalization (conflict management). For two sources S_1 and S_2 having respectively m_1 and m_2 as BBA, the conjunctive rule is defined as:

$$m_{\bigcirc}(A) = \sum_{B \cap C = A} m_1(B) \times m_2(C) \qquad \forall A \subseteq \theta. \tag{4}$$

A normalized version of conjunctive rule proposed by Dempster [3] integrates a conflict management approach that redistributes the generated conflictual mass. The Dempster's rule is defined as follows:

$$m_{\oplus}(A) = \frac{1}{1 - K} \sum_{B \cap C = A} m_1(B) \times m_2(C) \qquad \forall A \subseteq \theta, A \neq \emptyset \tag{5}$$

where K, representing the conflict mass between m_1 and m_2, is defined as:

$$K = \sum_{B \cap C = \emptyset} m_1(B) \times m_2(C) = m_{\bigcirc}(\emptyset). \tag{6}$$

Assuming that an information source has a reliability rate equal to $(1 - \alpha)$ where $(0 \leq \alpha \leq 1)$, such a meta-knowledge can be taken into account using the discounting operation introduced by Shafer [15], and defined by:

$$\begin{cases} m^\alpha(B) = (1 - \alpha) \times m(B) \qquad \forall B \subseteq \theta \\ m^\alpha(\theta) = (1 - \alpha) \times m(\theta) + \alpha \end{cases} \tag{7}$$

A discount rate α equal to 1 means that the source is not reliable and the piece of information that it provides cannot be taken into account. On the contrary, a null discount rate indicates that the source is fully reliable and the piece of information it provides is entirely trustable. Thanks to the discounting, an unreliable source's BBA is transformed into a function assigning a larger mass to θ.

III. RELIABILITY MEASURE AND DISCOUNTING

In the framework of the belief function theory, the measure K (equation 6) is often used as the only measure to quantify the conflict. However, it is not always satisfactory because it does not take into account all conflictual situations [15]. To highlight this behavior, let's consider the auto-conflict measure defined in [13] which proves the existence of another conflict origin. The auto-conflict of order n for one expert is given by:

$$a_n = (\bigcirc_{i=1}^n m)(\emptyset) \tag{8}$$

As it is shown, the conflict may appear from the source itself, i.e. the confused nature of a BBA.

In the following, several conflict measures (or discordance measures) developed in the framework of belief functions

are presented. These measures can be classified into two categories:

- The measures which allow the estimation of the confusion rate of a source and which will be called *Intrinsic measures* in the remainder.
- The measures which allow the evaluation of the discordance between two bodies of evidence and will be labeled as *Extrinsic measures*.

A. Intrinsic measures

The Intrinsic conflict measures the consistency between the different focal elements inside a BBA. Several measures have been proposed in the literature. These measures take into account the inclusion relations between the focal elements present in a BBA. Nevertheless, auto-conflict is a kind of contradiction measure that depends on iteration number (order), it was therefore necessarily to define an independent measure that dissociates from this constraint. In [16], the authors introduced a contradiction measure that no longer depends on order. Many Intrinsic distances were proposed such as the the confusion distance introduced by [7]. Another approach was presented by Daniel [2] using the normalized plausibility transformation to assess the internal conflict given by:

$$Pl\_IntC(m) = 1 - \max_{\omega \in \theta} Pl(\omega). \qquad (9)$$

Starting from this definition, there are many BBA without any internal conflicts: all BBA having $X \subseteq \theta$, $Pl(X) = 1$. There are some examples of BBA having no internal conflict: categorical[1], simple support[2], consonant BBA[3]. Finally all BBA, whose all focal elements have non-empty intersection, have no internal conflict.

B. Extrinsic measures

Several measures of Extrinsic conflict have been studied in order to model the disagreement between sources. Indeed, if one source opinion disagrees another, their fusion will lead to an important conflictual mass. In [14], an adaptation of existing distances as the Euclidean and the Bhattacharyya distance were introduced. Another extension of Euclidean distance is given by [1]. In [20], Tessem introduced a distance measure between the pignistic probabilities that are associated to mass functions. Other distances were studied to define distance between two BBA as the sum of differences of conflicting normalized plausibility masses [2]. Some authors have directly defined distance between different mass functions such as [9] that has the advantage of taking into account the cardinality of focal elements. This distance fulfills the metric axioms and is an appropriate measure of the contradiction between two BBA. Jousselme's distance [9] can be written as follows:

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

[1]A BBA with only one focal element A is said to be categorical and is denoted $m(A) = 1$.

[2]A BBA is said to be simple if m has no more than two focal sets, θ included.

[3]A BBA is said consonant if focal elements are nested.

where:

$$D(A, B) = \begin{cases} 1 & \text{if} \quad A = B = \emptyset \\ \frac{|A \cap B|}{|A \cup B|} & \text{if} \quad A, B \subseteq 2^\theta. \end{cases} \qquad (11)$$

For further details, the interested reader may refer to [10].

C. Conflict measures and discounting

Several works have been carried out to discount the BBA [5] but these studies are usually based on a learning database. Very few studies used measures of conflict to adapt the belief functions and in this case the measures used are Extrinsic measures of conflict.

The first use of Extrinsic measure, to discount the belief functions, was achieved by Deng et al. [4]. Initially, in this approach, a similarity matrix is built between belief functions. Then, the values of this matrix are used to weight the BBA.

Martin et al. [12] propose using a function that quantifies the conflict between BBA. This function, called $Conf(.,.)$, is defined as :

$$Conf(i, E) = \frac{1}{M-1} \sum_{k=1; i \neq k}^{M} Conf(i, k) \qquad (12)$$

with M is the number of belief functions produced respectively by M sources called $S_1, \ldots, S_M$ and E is the set of BBA such that $\{m_k | k = 1, \ldots, M$ and $k \neq i\}$. The function $Conf(i, k)$ is obtained using a BBA distance introduced by Jousselme et al. [9] (eq 10):

$$Conf(i, k) = d(m_i, m_k). \qquad (13)$$

The value $Conf(i, E)$ quantifies the average conflict between the BBA m_i and the BBAs of the set E. Once the conflict measure is obtained, the authors have proposed to compute discounting rates as follows:

$$\alpha_i = f(Conf(i, M)) \qquad (14)$$

where f is a decreasing function. The authors propose to choose the function f as follows:

$$\alpha_i = (1 - Conf(i, M)^\lambda)^{1/\lambda} \qquad (15)$$

with $\lambda > 0$. The authors in [12] recommend setting λ to 1.5. Extensions of this work use the idea of sequential discount to manage the conflict when combining belief functions [11].

To the best of our knowledge, no discounting measure was proposed for source reliability estimation based on both conflict origins (Intrinsic and Extrinsic conflict). Indeed, a source can be reliable even if it is in contradiction with other sources. In fact, the source can also be considered as reliable if it presents a non confused BBA. In this work, we take this hypothesis into consideration by not only using Extrinsic measures (as it is usually the case) but also integrating Intrinsic measure to estimate reliability. In the following, we introduce the Generic Discounting Factor (GDF) which estimates the source reliability based on an Intrinsic and Extrinsic measure.

IV. GENERIC DISCOUNTING FACTOR

The proposed discounting approach aims at discarding the contradictory and non reliable sources that can eventually lead to an important conflict in the fusion resulting BBA. Let's assume the frame of discernment θ containing all possible answers for a question Q relatively to sources $S_1, \ldots, S_n$. During the fusion stage, to each processed BBA is assigned a new discounting factor indicating its relevance and its global reliability.

We propose a new method for calculating discounting factors using the valuable information of the source confusion rate and belief function distance. The discounting factors are obtained by the use of a function f fulfilling some constraints:

- f is a increasing function from $[0,1]^2 \to [0,1]$
- $f(1,1) = 1$ and $f(0,0) = 0$.

Since this function allows taking in consideration the contraction of each source and the distance between them, it should integrate weight factors allowing the user to favor one distance measure to the other. The function f can be written as follows:

$$f := [0,1]^2 \to [0,1] \qquad (16)$$

$$(\delta, \beta) \to \frac{k.\delta + l.\beta}{k + l} \qquad (17)$$

where $k > 0$ and $l > 0$ are the weight factors. In this equation, δ denotes the internal conflict measure of the treated source indicating its confusion rate and β is the average distance between the treated source S_i and S_j with $j \in [1, \ldots, i-1, i+1, \ldots, M]$. We use Jousselme's distance defined in section III-B, which is commonly of use in belief measure works. Nevertheless, other Intrinsic and Extrinsic distances variants can be used. So, the values δ and β can be defined by:

$$\delta = Pl\_IntC(m_i) \qquad (18)$$

$$\beta = d(m_i, \overline{m}) = \frac{\sum\limits_{j \in [1,..,M] \setminus i} d(m_i, m_j)}{M - 1}. \qquad (19)$$

The function f can be then written as follows:

$$f := [0,1]^2 \to [0,1] \qquad (20)$$

$$(\delta, \beta) \to \frac{k.Pl\_IntC(m_i) + l.\frac{\sum\limits_{j \in [1,...,M] \setminus i} d(m_i, m_j)}{M-1}}{k + l}. \qquad (21)$$

The determination of the weight factors can be found automatically by minimizing the following constraints:

$$\begin{cases} k > 0 \quad and \quad l > 0 \\ E_{bet}(k,l) = \sum\limits_{i=1}^{I} \sum\limits_{n=1}^{N} (BetP^{(i)}(H_n) - U_n^i)^2 \end{cases} \qquad (22)$$

where $BetP^{(i)}$ represents the pignistic probability of x^i (vector to classify) from the learning base and U_n^i represents the x^i membership.

The classical discounting can be written as follows:

$$\begin{cases} m^{GDF}(B) = (1 - f(\delta, \beta)) \times m(B) \qquad \forall B \subseteq \theta \\ m^{GDF}(\theta) = (1 - f(\delta, \beta)) \times m(\theta) + f(\delta, \beta) \end{cases}. \qquad (23)$$

Thus, based on the conjunctive sum (equation 4), the combination with a GDF discounting becomes:

$$m_{\bigodot}(A) = \sum_{B \cap C = A} m_1^{GDF}(B) \times m_2^{GDF}(C). \qquad (24)$$

Example:
Let's consider the frame of discernment $\theta = \{H_1, H_2\}$ and three sources S_1, S_2 and S_3. For the considered sources, the GDF discounting factors are computed as shown by Table I:

TABLE I
GDF CALCULATION EXAMPLE

	S_1	S_2	S_3
H_1	0.3	0.4	1
H_2	0.3	0.4	0
θ	0.4	0.2	0
Intrinsic conflict: δ	0.3	0.4	0
Extrinsic conflict: β	0.3193	0.3050	0.5242
GDF: $f(m)(k = l = 1)$	0.3066	0.3525	0.2621

As sketched by the statistics of Table I, the GDF considers S_3 as the most reliable source despite being distant to S_1 and S_2 (a classical discounting approach would reject S_3 for being distant). Thanks to its categorical constitution making it without any Intrinsic conflict, S_3 is considered as a reliable source. The same explanation can be applied on S_1 and S_2 where despite being close, none of them can reinforce any hypothesis.

V. EXPERIMENTAL EVALUATION

In this section, we introduce a classifier based on belief function formalism. The proposed approach for classification takes into consideration the multi-source context and estimates their reliability before any fusion process. The proposed classifier is applied on several benchmarks in order to test its accuracy.

A. The GDF classifier

In order to integrate the GDF measure into a belief function classifier, we distinguish two main family approaches. Likehood based approaches [15], rely on density estimation where they assume known the class-conditional probability densities for each class. The second family, is the distance based approaches [22]. Both methods are applicable, but we have chosen to work with the distance based model for its simplicity of its generated BBA.

As it is shown in Figure 1, the GDF classifier is composed of two parts. The first part, where belief functions are estimated, BBA's are constructed following distance based model introduced by Zouhal and Denœux in [22]. This estimation approach depends on a training set where each vector, constituting it, is considered as a piece of information. For each instance x to classify, we apply the K Nearest Neighbor (KNN) to retain only close vectors in terms of characteristics. Each vector x_i, found by the KNN, constitutes a piece of information regarding x membership to H_n (x_i class). The more x is close to x_i, the higher the belief value assigned to
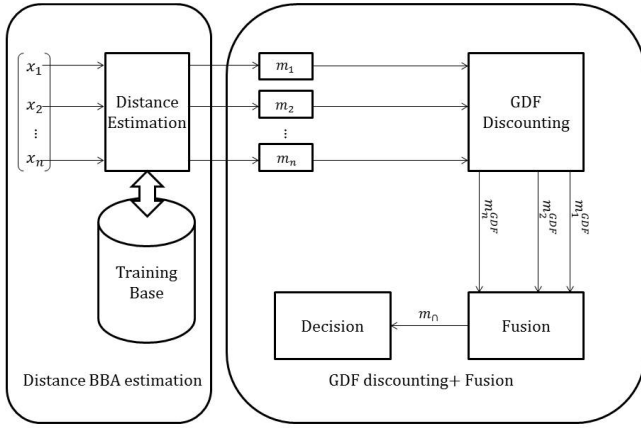
Fig. 1. The proposed GDF classifier diagram

Data set	#Instances	#Attributes	#Classes
Iris	150	4	3
Wine	178	13	3
ILPD (Indian Liver Patient Dataset)	583	10	2
Diabetes	767	9	2

analyze the difference between the proposed approach and the Distance Classifier (DC). Since each tested method is based on the KNN algorithm, we fixed $K = 4$ for all of them. Table III, shows classification results of tested classifiers where '#' and '%' indicate respectively the number and the pourcentage of correct classified instance.

	DC		GDF		Mart		KNN	
	#	%	#	%	#	%	#	%
Iris	147	98,00%	**148**	**98,66%**	147	98%	143	95,33%
Wine	154	86,51%	158	88,76%	151	84,83%	**169**	**94,94%**
ILPD	388	66,55%	**392**	**67,23%**	391	67,06%	378	64,83%
Diabete	538	70,05%	**541**	**70,44%**	538	70,05%	539	70,18%

The GDF classification accuracy is better than Martin et al's approach in every treated data set. This improvement highlights the importance of using the Intrinsic measure to estimate the reliability of a source. We also improve the DC's results which also proves the contribution of GDF in the classification process. The integration of a discounting stage before combination allows unreliable source discarding for a better decision. By comparing ourself to KNN classifier, we notice that we have also improved its result for the Iris, ILPD and Diabete data sets. This improvement can be interpreted as the contribution of uncertainty modeling and multi-source fusion. However, for the Wine data set, the KNN which presents the best results.

H_n^i is. For each element x_i sufficiently close to x, a BBA estimation model can be constructed as follows:

$$\begin{cases} m_i(\{H_n\}) = \alpha^i \phi^i(d^i) \\ m_i(\theta) = 1 - \alpha^i \phi^i(d^i) \end{cases} \quad (25)$$

where $0 < \alpha^i < 1$ is a constant. $\phi^i(.)$ is a decreasing function fulfilling $\phi^i(0) = 1$ and $lim_{d\to\infty}\phi^i(d) = 0$, d_i is the Euclidian distance between the vector x and x_i. The ϕ^i function might be an exponential function following this form:

$$\phi^i(d^i) = exp(-\gamma^i(d^i)^2) \quad (26)$$

where γ^i is a positive parameter. A learning algorithm was proposed by Zouhal and Denœux [22] for determining the parameters γ^i in the equation (26) by optimizing an error criterion. The resulting I BBA combined via Dempster's combination rule (eq 5) constitute the *Distance Classifier* (DC). For GDF classifier, as illustrated in the second part of Figure 1, the resulting belief functions are discounted then combined. Indeed, on each resulting BBA m_i, a GDF discounting (eq 23) and combination are applied following this formula:

$$m = \oplus_{i\in[1,...,I]}m_i^{GDF}. \quad (27)$$

B. Experimental results

The experimentation of the GDF classifier was carried out on several UCI benchmarks [6]. The characteristics of these data sets are summarized in Table II. For the classification task, we applied a cross-validation technique. Each instance up to be classified is tested using a training set pruned from it.

The results will be compared to several referenced works. Since we are proposing an oriented discounting conflict management approach, we compare ourselves to Martin et al. work [12] (described in section III-C) which has been shown that it outperforms its predecessors by its good performance. In order to get a general idea about our belief formalism classifier, we
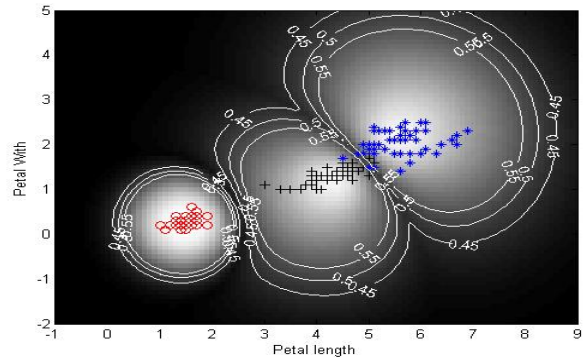

Fig. 2. Pignistic probability maxima for DC approach in Iris Base

In the following, we compare the belief based classification methods. Figures 2, 3 and 4 show the different elements of Iris training base studied according to their petal width and length. In those Figures, we illustrate the iso-pignistic curves
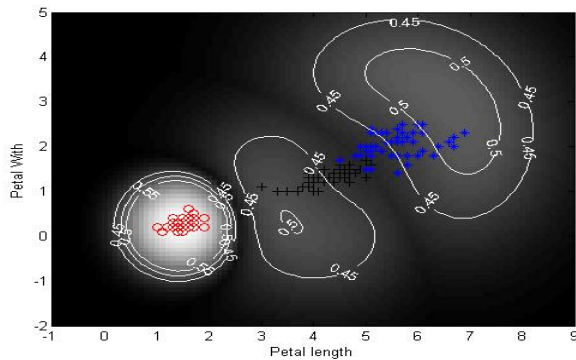
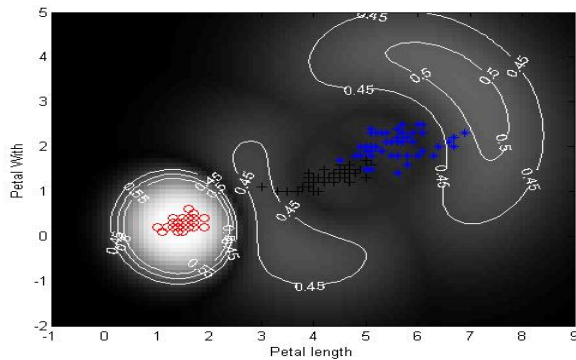Fig. 3. Pignistic probability maxima for GDF approach in Iris Base

Fig. 4. Pignistic probability maxima for Martin's approach in Iris Base

where bright zones correspond to a high pignistic probability values whereas the dark one indicates the opposite. For Iris-setosa vectors (red colored in Figures), we notice that pignistic probability is the same for every classification method thanks to the class uniformity of all extracted neighbors. For the two other classes, we remark several differences between studied approaches specially in the bordering area. The DC approach (Figure 2), class change is operated roughly leading to classification errors in decision stage. However, GDF and Martin's approaches (Figure 3 and 4) present a low pignistic probability in borders. This result is a natural consequence of discounted BBA that contributes in representing better the doubt between both classes. For Martin's discounting the doubt zone is the largest where the GDF rejects less vectors in decision.

VI. CONCLUSION

In this paper, we present a new method to estimate source reliability in a multi-source belief function theory context. Two main family BBA measures can be distinguished. Intrinsic measures that estimate BBA confusion about an instance membership. The second is the Extrinsic measures that estimate distance between two different BBA related to the same instance. The proposed method integrates those two type of measures to elaborate the GDF discounting system.

GDF was integrated in a multi-source distance classifier. The contribution was validated on several benchmarks data set comparatively to different referenced works. In future work, further Intrinsic and Extrinsic measures can be investigated in order to optimize discounting performance. Additionally, further conflict origins can be studied like lying and insincere sources.

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