Belief function classification with conflict management: application on forest image

Ahmed Samet*
*Univ. Lille Nord de France, ULCO
EA 4491 LISIC, F-62228
Calais, France
Email:samet@lisic.univ-littoral.fr

Eric Lefèvre †
†Univ. Lille Nord de France, UArtois
EA 3926 LGI2A, F-62400
Béthune, France
Email:eric.lefevre@univ-artois.fr

Sadok Ben Yahia ‡
†Univ. Tunis El Manar
LIPAH
Tunis, Tunisia
Email:sadok.benyahia@fst.rnu.tn

***Abstract*—Treating imprecise and uncertain data requires an adequate formalism allowing a fit modelization. Several formalisms can be identified such as Bayesian theory, fuzzy set theory and belief function theory. The belief function theory provides an adequate formalism to manipulate those imperfect data. It also allows source fusion thanks to the combination operators that it integrates. The fusion process generates an empty set mass denoted *conflict* that illustrates the contradiction rate between considered sources. In this work, we tackle the classification of a forest high-resolution remote-sensing image problem. In order to classify this image, we handled imperfect information with the belief function theory. We propose a method for classification based on belief function theory and source fusion. The introduced Redistributing Conflict Classification Approach (RCCA) analyzes the conflict resulting from the fusion and redistributes it to the most pertinent classes. An experimental comparison to well known literature classifiers is provided.**

***Keywords*—belief function theory; information fusion; classification; conflict management**

I. Introduction

The progress known by the image acquisition techniques had an important impact on the precision and the detail in remote-sensing images. This gain in detail in high-resolution images had a negative incidence on the volume of treatment and data complexity. These constraints urged the research community to find solutions to manage the important quantity of information and data.
Acquired high-resolution images are crippled with imperfection [1]. To handle such type of data, several formalisms exist such that fuzzy [2] and belief function theory [3]. Indeed, the latest theory offers a fit formalism for such type of data and handles multi-source problems thanks to the combination operators that it integrates. Several works have associated the pattern recognition domain to belief function theory [4] providing interesting results.
In this context, we tackle a problem of high-resolution remote sensing classification of a forest typed images. We benefit from the belief function theory to modelize imperfect sources that exist in the image. In this work, we take on the problem of belief function estimation and we introduce a forest image classification method based on belief distance classifier [5].
As shown in [1], combining multiple sources could generate a mass assigned to the empty set denoted *conflict*. The conflict is an alarm about the contradiction existing between sources [6] but also needs to be managed. In this work, we propose a new method for classification improvement based on conflict redistribution. Indeed, the resulting conflict is treated and redistributed to pertinent classes guided by retrieving weighting factors for the generic framework [7].
The paper is organized as follows. Section II describes the mathematical background of belief function theory for information fusion. It defines various ways to combine opinions. In section III, the proposed approach for tree crown's classification based belief distance classifier is introduced. Section IV sheds light on the proposed conflict management approach that is based on the generic framework. Retrieving the weighting factors needed for conflict redistribution is detailed. Section V reports the encouraging results of the experimental validation by confronting it to the classical approaches of the literature. In Section VI, we conclude and we sketch issues of future work.

II. Belief function theory

The Belief Function Theory was initiated by the work of Dempster [3] on the upper and lower probabilities. The development of the theory formalism is due to Shafer [8] which has shown the benefits of belief functions theory to model uncertain knowledge. In addition, it allows knowledge combination obtained through various sources. The belief function theory is based on several concepts. In the following, we present the main concepts of this theory.

A. Frame of discernment

The frame of discernment is the set of possible answers for a treated problem and generally noted Θ. It is composed of N exhaustive and exclusive hypotheses:

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

The exhaustive assumptions means that the solution of the problem is necessarily one of the hypotheses H_i from frame of discernment. The exclusivity condition support the unicity of the solution $H_i \cap H_j = \emptyset \quad \forall i \neq j$. From the frame of discernment Θ, we deduce the set 2^Θ containing all the 2^N subsets A of Θ:

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

This set constitutes a reference to assess the veracity of any proposal.

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:

$$\begin{cases} \sum\limits_{A \subseteq \Theta} m(A) = 1 \\ m(\emptyset) = 0. \end{cases} \tag{1}$$

Each subset X of 2^Θ fulfilling $m(X) > 0$ is called a *focal element*.

C. Discounting

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 [8], and defined by:

$$\begin{cases} m^\alpha(B) = (1-\alpha) \times m(B) & \forall B \subseteq \Theta \\ m^\alpha(\Theta) = (1-\alpha) \times m(\Theta) + \alpha. \end{cases} \tag{2}$$

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 true. Thanks to the discounting, an unreliable source's BBA is transformed into a function assigning a larger mass to Θ.

D. Combination operators

In the following, we present several combination operators allowing sources fusion.

1) Conjunctive sum: Proposed within the Transferable Belief Model [9], the conjunctive sum combines several information. For two sources S_1 and S_2 having respectively m_1 and m_2 as BBA, we write the conjunctive sum $m_{\textcircled{\cap}}$ in the following form:

$$m_{\textcircled{\cap}} = m_1 \textcircled{\cap} m_2. \tag{3}$$

For an event $m_{\textcircled{\cap}}(A)$ can be written as follows:

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

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:

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

$m(\emptyset)$ is called the *conflictual mass*. A BBA is called *normal* whenever the empty set is not a focal element and this corresponds to a closed world assumption [9], otherwise it is said *subnormal* and corresponds to an open world assumption [9].

2) Generic framework: Several works tackled grouping conflict operator in order to profit from their complementary contributions [7], [10], [11], [12], [13]. From those operators, we distinguish the *Generic framework*, which generalizes the conflict redistribution and unifies several redistribution rules.

Introduced by Lefevre et al. [7], the generic framework aims at distributing the conflictual mass $m_{\textcircled{\cap}}(\emptyset)$ on a set of propositions P according to a weighting factor $W(A,m)$ ($A \subseteq P$) with $m = \{m_1, ..., m_j, ..., m_J\}$. The final mass after fusion (combination), for a proposition A, is the sum of both masses:

$$\begin{cases} m(A) = m_{\textcircled{\cap}}(A) + m^c(A) & \forall A \subseteq \Theta \\ m(\emptyset) = 0. \end{cases} \tag{7}$$

m^c is part of the conflicting mass and can be written as follows:

$$\begin{cases} m^c(A) = W(A,m) \cdot m_{\textcircled{\cap}}(\emptyset) & \forall A \subseteq P \\ m^c(A) = 0 & otherwise \end{cases} \tag{8}$$

such that:

$$\sum_{A \subseteq P} W(A,m) = 1. \tag{9}$$

The generic framework presents the largest representation for any conflict management approach. In fact, it does not only provide the largest framework for conflict management but also the possibility to customize the empty set mass redistribution using the weighting factors. This characteristic makes the generic framework flexible and suited in case of existence of an additional information.

E. Decision: Pignistic probability

The pignistic probability, denoted $BetP$, was proposed by Smets and Kennes [9] 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:

$$BetP(H_n) = \sum_{A \subseteq \Theta} \frac{|H_n \cap A|}{|A|} \times m(A) \qquad \forall H_n \in \Theta. \tag{10}$$

III. Distance classifier: Application on high-resolution forest image

In the following, we introduce the based distance classifier that was adapted and applied of forest image classification problem. The proposed classifier relies on multi-source fusion. Several belief based classifiers exist such that the likelihood [8] and the tree based classifiers [14]. In our case, we built our classifier on the distance classifier [15] for its simplicity and combinatorial explosion avoidance. The properties of this classifier is detailed and compared in [16].

A. Distance estimation model classifier

In order to profit from the large amount of data constituting our learning base, we opted for the Zouhal et al. [5] distance BBA estimation model. The presence of a training pattern x^i, having the class $\{H_n^i\}$, among the K Nearest Neighbors (KNN) of under classification pattern x is considered as a piece of evidence. Indeed, it influences our belief concerning

the class membership of the entity under consideration. This information is represented by a BBA m over the set Θ of classes. A fraction of the unit mass is assigned by m to the singleton $\{H_n^i\}$, and the remaining is assigned to the whole frame of discernment Θ. The mass $m(\{H_n^i\})$ is defined as a decreasing function of the distance d between x and x^i in the feature space. The K nearest neighbors of x can be regarded as K independent sources of information represented by BBA. These several pieces of evidence can be aggregated by means of Dempster's combination rule to represent our belief concerning x class membership.
The adopted strategy consists in modeling the information according to every characteristic x_j (with $j \in [1, J]$) of the vector x to classify. A belief function m_{sj} is then defined by [17]:

$$\begin{cases} m_{sj}(\{H_n\}) = \alpha_j^s \phi_j^s(d_j^s) \\ m_{sj}(\Theta) = 1 - \alpha_j^s \phi_j^s(d_j^s) \end{cases} \tag{11}$$

where $0 < \alpha_j^s < 1$ is a constant, d_j^s represents the distance between the j-th component x_j of the vector x and its neighboring vector v_s ($s \in [1, K]$). The function ϕ_j^s can be expressed in the following way:

$$\phi^s(d_j^s) = exp(-\gamma_j^s (d_j^s)^2). \tag{12}$$

A learning algorithm was proposed by Zouhal et al. [5] for computing the parameters γ_j^s in the Eq. (12) by optimizing an error criterion.

Dempster's combination is used to combine those K belief functions. m_j is the resulting belief function and it is equal to:

$$m_j = \oplus_{s \in [1,K]} m_{sj}. \tag{13}$$

A unique belief function m is obtained by the application of the same fusion principle on those resulting J BBAs:

$$m = \oplus_{j \in [1,J]} m_j \tag{14}$$

with J standing for number of sources.

B. Forest image based belief classifier

In the following, defining a BBA to each extracted tree crown from the forest scene is detailed [1]. Since we are dealing with composite sources, the choice of multidimentional model was the most appropriate. Also in order to profit from the large amount of data constituting our learning base, the distance model which integrates the distance measure helpful for BBA construction was chosen. Let us consider Θ the frame of discernment constituted by four classes $\{Zen\ Oak, Cork\ Oak, Arboretum, Coniferous\ tree\}$. Those four classes constitute the main tree's type existing in the image. Three different information sources are distinguished in the image. The *Spectral*, *Texture* and the *Structural* sources are used in the source fusing problem and are defined as follows:

- Spectral information: this source study the tree crown relatively to its level of grey mean.
- Texture information: a composite source which analyzes the tree crown by their gray level organization. The studied textural features are *Mean*, *Variance*, *Energy*, *Contrast* and the *Entropy*.
- Structural information: a composite source which analyzes the tree crown by their shape. The studied structural features are *Area*, *Diameter*, *Perimeter* and the *Wellepsy*.

TABLE I. DISCOUNTING COEFFICIENT FOR TEXTURE SOURCE CHARACTERISTICS.

	Mean	Variance	Energy	Contrast	Entropy
Discounting coefficient	0.4	0.4	0	0	0.5

TABLE II. DISCOUNTING COEFFICIENT FOR STRUCTURE SOURCE CHARACTERISTICS.

	Area	Diameter	Perimeter	Wellepsy
Discounting coefficient	0.4	0.4	0	0

For each one of the three information fusing source, we apply a KNN belief function estimation (Eq. (11)). Each feature gives four BBAs ($K = 4$) which are combined via the Dempster's combination rule (Eq. (13)). The result is a single BBA expressing the crown membership from the point of view of the considered composite source. We associate to each composite source BBA a reliability factor. These coefficients are obtained through experiments and by studying each characteristic individually. The percentage of good classification is our discounting coefficients (Table I and II). The same procedure is operated on the three sources. Their discounting coefficients are shown in Table III.

The gathered ten source's BBA are also combined through (Eq. (14)) to get the final tree crown's BBA. In the sequel, the described Distance Model Classifier is denoted DMC. In order to observe the concordance between fused sources, we replace the Dempster's rule in Eq. (14) by the conjunctive sum (Eq. 4). The resulting conflict is an indicator about contradiction between proposition brought by fused sources and might be in help afterward in classification improvement. Interested reader may refer to [1] for further details.

IV. AUTOMATIC SEEK OF WEIGHTING FACTORS FOR CONFLICT MANAGEMENT

In this section, we detail the contribution of interpreting and using the conflict resulting from the conjunctive combination of several information sources. Analysing the conflict and redistribute it on probable classes was studied in [18], [7]. In this paper, we study the origins of the conflict resulting from the combination of tree crown BBAs. Once the origin is identified, we propose a method to redistribute conflict on the probable class through a conflict management approach. This method is called RCCA for Redistributing Conflict Classification Approach. Several operators for the conflict management

TABLE III. DISCOUNTING COEFFICIENT FOR THE CONSIDERED SOURCES.

	Texture	Spectral	Structure
Discounting coefficient	0.4	0	0.2

TABLE IV. REGISTERED CONFLICT FOR STUDIED TREE CROWNS

	[0, 0.2)	[0.2, 0.4)	[0.4, 1)
Conflict rate	12%	14%	74%

exist in the literature allowing treating and managing the conflictual mass [19]. Among these operators, we identify the generic framework which distinguishes by its unifying formalism. In the following, we present a method that aims to seek automatically the weighting factors depending of the analyzed area in the image.

A. Motivation

Several studied regions from the image present a high conflict values generated after the sources' fusion. As it is shown in Table IV, the conflict value exceeds the 0.4 in 74% of tree crown's BBA that could lead afterward to classification errors. This conflict appears with different rates depending the studied tree crown. The highest values of conflict are registered for the Arboretum areas. This means that the fused sources (i.e., spectral, textural and structural) are in contradiction. This conflict highness is interpreted as the result of the similarity existing between the Arboretum class and the other trees in the frame of discernment. This proves the importance of using an adequate conflict management approach in order to differentiate between classes.

B. Region determination of weighting factors for conflict management

Even if the generic framework is able to unify many classical operators of combination, the determination of weighting factors remain a problem that has to be solved. In the following, the Redistributing Conflict Classification Approach (RCCA), that is based on computing the generic framework's weighting factors, is detailed.

1) Conflict inductive class: This method is based on the existence of a class that generates conflict after the combination phase. This class is denoted $C_{conflict}$. The $C_{conflict}$ class has many resemblances with the other classes (reason for conflict appearance) but it distinguishes by a regional characteristic making it unique and recognizable. Those ascertainment have led us to identify the Arboretum as the $C_{conflict}$ class. We also studied the image by areas to verify the membership of each region to the $C_{conflict}$ class. To find correctly the weighting factor needed for the conflict management approach, we study the image following the frame of discernment $\Omega = \{C_{conflict}, \overline{C_{conflict}}\}$. Our proposed approach relies on studying the membership of each region according to its texture value. For this purpose, we calculate the belief function for each considered region in Ω. The calculated BBA is important to decide how to compute the weighting factors.

2) Region belief function estimation: Let's consider $\Omega = \{C_{conflict}, \overline{C_{conflict}}\}$ the frame of discernment. For each analyzed region R in the image, we create a belief function that summarizes its membership rate to $C_{conflict}$ class. This BBA can be written as follow:

$$\begin{cases} m_R^{\Omega}(C_{conflict}) = \beta(d) \\ m_R^{\Omega}(\Omega) = 1 - \beta(d) \end{cases} \tag{15}$$

such that β is a function that depends on a distance value d that could be inspired from Eq.12. This BBA is built by adopting the growing region approach to bound regions belonging to $C_{conflict}$. The belief mass is found by the use of distance estimation approach (see section III). For each studied region, a BBA is modelized such that Eq.15. If the BBA confirms that the region belongs to the $C_{conflict}$ class the studied region is expanded. The same principle is done to the expanded region. The estimation of the BBA requires a distance d between the studied region and a theoretical value (prototype). The theoretical value is provided by a graph that indicates the theoretical texture value for each region size. In this work, we studied the expansion of the energy characteristic (texture information) for different region window size. A region is considered belonging to $C_{conflict}$ if its granted belief (Eq. 15) is greater than a confidence threshold min_{conf} fixed in the beginning. In case of the studied region belong to $C_{conflict}$ by verifying the min_{conf} condition, the region is expended. The analysis of the texture of those regions, as shown in the Figure 1, illustrates the highness of the energy. This figure constitutes a learning base that we applied to calculate the belief mass (Eq. 15) using a distance prototyped estimation approach (see section III). The estimation of those belief function is detailed in Algorithm 1. Indeed, $seek\_texture\_region$ function computes the texture energy of a region R while $euclidean\_distance$ function estimates the distance d between the studied region and a theoretical value.

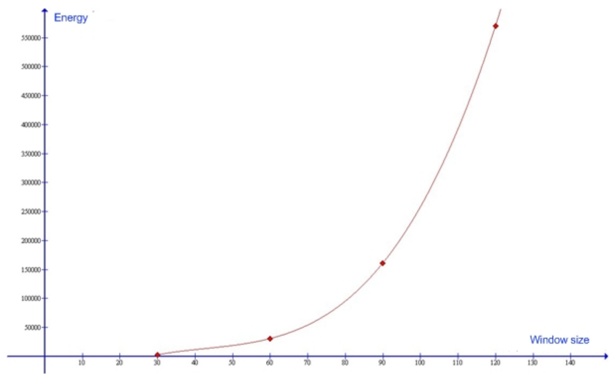

Fig. 1. The energy value evolution depending on the image window size

Algorithm 1 Belief function estimation

Require: R
Ensure: m_R^{Ω}
$value \leftarrow seek\_texture\_region(R)$
$distance \leftarrow euclidean\_distance(value, Energy(size(R)))$
$m_R^{\Omega}(C_{conflict}) \leftarrow \exp(-\gamma_q \times distance^2)$
$m_R^{\Omega}(\Omega) \leftarrow 1 - m_R^{\Omega}(C_{conflict})$

3) Determination of the weighting factors: The assignment of the weighting factors depends on the studied region BBA. The determination of weighting factors is made only when the size of the analyzed region exceeds a threshold fixed by experiments. In these cases, for $m_R^\Omega(C_{conflict})$ greater than a fixed threshold, this region R will be considered as belonging to $C_{conflit}$ class. In that case, each tree crown's BBA m in R is assigned the following weighting factors:

$$\begin{cases} W(C_{conflict}, m) = m_R^\Omega(C_{conflict}) \\ W(\Theta, m) = m_R^\Omega(\Omega) \end{cases} \tag{16}$$

Otherwise, if $m_R^\Omega(C_{conflict})$ is less than the threshold, this area does not belong to the $C_{conflit}$ class and assignment of the weighting factors will be as follows:

$$\begin{cases} W(C_{conflict}, m) = 0 \\ W(\Theta, m) = 1 \end{cases} \tag{17}$$

This distribution is equivalent to transferring the conflict entirely on the assumption ignorance which corresponds to Yager's conflict management approach [20]. The Algorithm 2 details the conflict management approach for weighting factors determination.

Algorithm 2 Weighting factors determination

Require: $Arboretum\_trees\{A_1, ..., A_n\}, T\_size, min_{conf}$
Ensure: $weightingfactors\{W\_A_1, W\_\Omega_1, ..., W\_A_n, W\_\Omega_n\}$
for all $A_i \in Arboretum\_trees$ **do**
  $R \leftarrow Region(A_i)$
  repeat
    $R \leftarrow Growing\_region(R)$
    $\{m_R^\Omega\} \leftarrow Belief\_function\_estimation(R)$
  until $(m_R^\Omega(C_{conflict}) \leq min_{conf}$ **or** $size(R) \geq T\_size)$
  if $m_R^\Omega(C_{conflict}) \leq min_{conf}$ **then**
    $W\_A_i \leftarrow m_R^\Omega(C_{conflict})$
    $W\_\Omega_i \leftarrow 1 - m_R^\Omega(C_{conflict})$
  else
    $W\_A_i \leftarrow 0$
    $W\_\Omega_i \leftarrow 1$
  end if
end for

TABLE V. PERFORMANCE COMPARATIVE RESULTS: RCCA VS DISTANCE CLASSIFIERS.

Classifier	Zen Oak		Cork Oak		Arboretum		Coniferous tree	
	RCCA	DMC	RCCA	DMC	RCCA	DMC	RCCA	DMC
Zen Oak	**83.25%**	80.76%	13.57%	15.38%	0.00%	0.00%	3.18%	3.86%
Cork oak	22.60%	29.11%	**72.11%**	50.63%	0.00%	12.65%	5.29%	7.61%
Arboretum	1.89%	4.13%	15.17%	28.27%	**81.05%**	35.86%	1.89%	31.74%
Coniferous tree	16.66%	3.82%	39.91%	29.89%	0.00%	32.60%	**43.43%**	33.69%

The Algorithm 2 computes the weighting factors, such that for example $\{W\_A_1, W\_\Omega_1\}$ represents the weighting factors of each tree crown located in the neighborhood of A_1. The application of the *Growing_region* function increments the size of the studied region to add more tree crowns. The call for $Belief\_function\_estimation$ function allows to estimate the BBA for the studied region. The growing region process continues until we reach *T_size* or the studied region does not belong anymore to the $C_{conflict}$ class.

TABLE VI. LEARNING BASE SIZE OF THE USED INFORMATION SOURCES

	Spectral base	Texture base	Structural base
Size	4	233	264

V. EXPERIMENTAL RESULTS

We conducted experiments on the classification applied on a set of QuickBird Near InfraRed (NIR) forest images having 0.6m per pixel as resolution. Indeed, we applied our classification approach in order to classify the tree crowns. Our study zone is a forest region in the administrative district of Jendouba in Tunisia, more specifically the town of Ain-Drahim. The Table VI shows the size of the learning base for each source. For the spectral information source, we have only four elements since we implemented the distance estimation model-prtotype version. It means, rather than using several tree crowns spectral values as learning base, we use their average rate. Each class has its own spectral average value.

A. Classification and conflict management contribution

The image is segmented by the brownian motion approach [21]. The choice of learning zones was based on the information contained in the forest inventory. Indeed, the high resolution image was carved into several images. Some of them will be used to define our learning base and the other will be used to test the classification. In following, we present experimentally an assessment of the proposed RCCA approach contribution. In order to evaluate the contribution of RCCA, we are interested in comparing to a Distance Model Classifier (DMC) based on the distance belief estimation model and Dempster's combination (see Subsection III-A). Both methods rely on belief function theory classification.

The proposed Redistribution Conflict Classification Approach (RCCA in Table V) was applied on highly conflictual BBAs gathered from different forest scenes. Those BBAs represent 642 tree crowns. The results were compared to a Distance Model Classifier (DMC) based on the distance belief estimation model and Dempster's combination. The results show the benefits of using the generic framework as conflict manager. All good classification rates of all four classes have been improved drastically. Indeed, singling out the arboretum class and treating it individually has improved the result of other classes comparatively to the distance classifier. In the other hand, the generic framework proves that it is a good asset since it allows the personalize the conflict redistribution for a better classification.

The Figure 5, 6, 7 and 8 show the classification improvement for Arboretum. The region containing arboretum's trees is delimited with the growing region approach (see Subsection IV-B) then our redistribution conflict method is applied. As a result, we notice an important improvement in Arboretum classification by comparing Figure 6 and 8. Focusing our conflict management approach on the conflict inductive class (Arboretum class) also had an impact on other classes. Indeed, our method can decide whether a studied region belongs to the arboretum class. If it is not the conflict is redistributed to the ignorance Θ which also could improve the results. Indeed, Figure 3, 4, 9 and 10 attest of the cited improvement for the Zen and the coniferous tree classes.

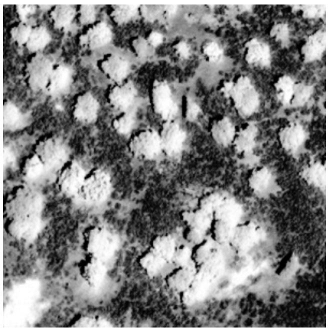

Fig. 2. Zen area.

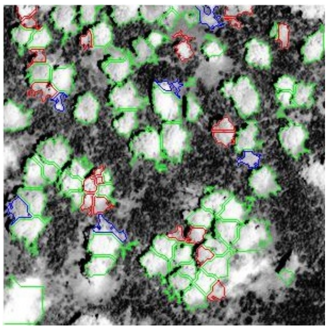

Fig. 3. Zen area DMC classification.

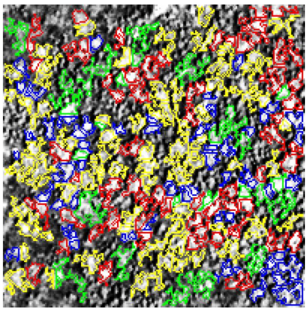

Fig. 9. Coniferous tree area DMC classification.

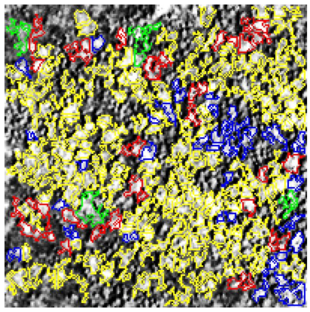

Fig. 10. Coniferous tree area RCCA classification.

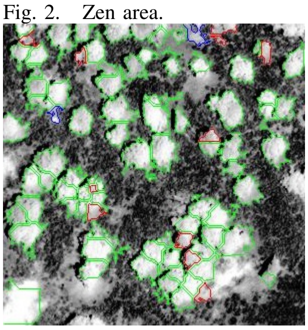

Fig. 4. Zen area RCCA classification.

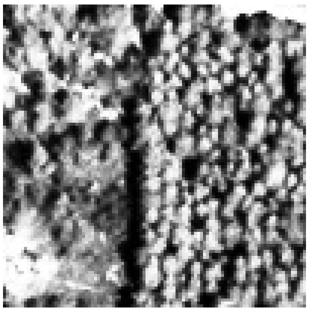

Fig. 5. Arboretum area.

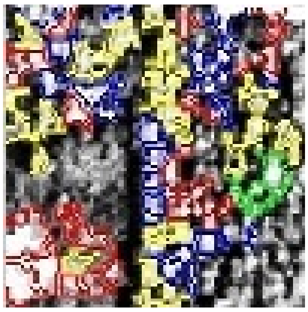

Fig. 6. Arboretum area with DMC classification.

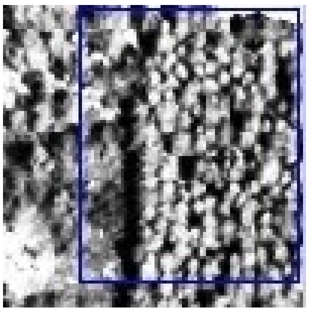

Fig. 7. Arboretum aera delimited with the growing region approach.

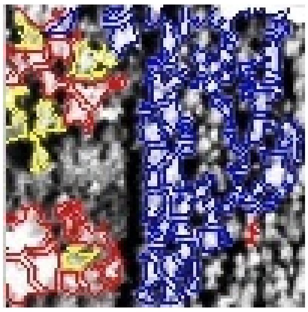

Fig. 8. Arboretum area with RCCA classification.

B. RCCA vs. the well known approaches of the literature

In the following, we compare the RCCA classifier to well known classifiers of the literature. The RCCA good classification rates are confronted to several known classifier results such as: the K Nearest Neighbour (KNN), Naive Bayes classifier, Neural Network and Decision Tree. The experimentation was conducted on the same database of 642 tree crowns. The results of the cited classifiers are provided by the of WEKA [22] through cross validation technique. They are summarized in Table VII in terms of good identification rates of the four classes.

Table VII shows that the RCCA provides the best classification results for the Zen oak and the Arboretum comparatively the other methods. This result can be interpreted as the conflict management contribution. Indeed, the RCCA operates a first classification and redistribute the conflict to the pertinent class following a conflict analysis. The learning stage is the the main the difference between the proposed approach and classical ones.

In addition, the RCCA is based on uncertainty representation with the belief function theory. Such kind of modelization allows a better representation of the tree crown membership. This assertion can be proved by comparing the KNN results to its belief variant DMC in Table V. On the other hand, we notice that comparing to a Neural Network bassed classifier, RCCA maintain an acceptable good average in the detection of cork oak. The coniferous tree detection rate of Neural Network based classifier is the best.

VI. Conclusion

In this work, we proposed a method to classify a forest high resolution image based on belief function theory and conflict redistribution. As a first step, we adapted the belief distance classifier on tree crowns found in the image. The important registered conflict, obtained after source fusion, have led us to redistribute it smartly for classification improvement. Therefore, we adapted the generic framework and we proposed an automatic method to compute the weighting factors required for conflict redistribution that we called RCCA. The determination of the weighting factors is based on region analysis around conflict inductive tree crown class. As illustrated in the experimentation section, the redistribution conflict based approach has improved drastically all good classification rates. Even the comparison of RCCA to well known classifier has provided interesting results. In future works, we study the automatic seek of those weighting factors based on every region spatial characteristics. Indeed, the association between data mining and conflict management could be interesting.

TABLE VII. COMPARATIVE RESULTS: RCCA VS KNOWN CLASSIFIERS.

	K Nearest Neighbour (KNN)	Naive Bayes	Neural Network	Decision Tree	RCCA
Zen oak	55.07%	52.90%	65.21%	62.32%	**83.25%**
Cork oak	68.27%	44.71%	86.54%	81.25%	**72.11%**
Arboretum	54.86%	68.75%	67.36%	50.69%	**81.05%**
Coniferous tree	42.10%	28.29%	55.26%	59.87%	**43.43%**

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