# INTEGRATION OF CONTEXTUAL INFORMATION FOR THE TRANSFER OF BELIEFS IN AN INFORMATION SOURCES FUSION SYSTEM – APPLICATION TO DETECTION AND CLASSIFICATION OF TREES CROWNS

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**ABSTRACT:**

In this paper, we present an approach based on the transferable belief model for the detection and the classification of trees crowns on very high resolution satellite images of forest scenes. The masses resulting from the high resolution image source don't always allow deciding between the classes of occupation satisfactorily. Forest context and information about the structure of the forest species are two key elements in the forest scenes classification process. We expose in this paper the retained modelling of the context concept and the approach of revising masses through a transfer of belief. Then, we give some experimentation that illustrates the given approach.

## 1. INTRODUCTION

Remote sensing images classification is confronted to the theoretical requirements of information sources fusion approaches. The existing models offer an interesting theoretical framework (J. Desachy and all, 2000). However, their application often emphasizes the incapacity of these methods to take into account the context. Context is traduced by determinant expert's knowledge and is considered in this paper not as elementary information but rather as a contextual constraint in the masses calculations specially those corresponding to belief masses functions revision. Indeed, analysis of the image pixel by pixel, often adopted as the basis of the classification process does not take into account the object to which the pixel belongs. But this information, that we call "contextual information", may be important for the classification process. It is the case of forest scenes images where the trees crowns delimit a subset of classes of occupation. The mass estimation of a scene point will thus have to take into account if this point is inside or outside the crown.

This paper exposes an approach allowing taking into account the context in the evaluation of the masses. We present also the manner with which we modeled this problem. An application on high resolution images (HRI) emphasized results very close to the field reality.

The approach that we propose uses belief functions theory as fusion formalism. We apply a beliefs transfer based on contextual information. In the following section, we tried to summarize the basic notions of both belief functions theory and transferable belief model. These concepts are essential for the explanation of the stages of our approach detailed in section 3.

## 2. BELIEF FUNCTIONS THEORY

The belief functions theory was named at the beginning with the name of its authors: Dempster and Shafer (Shafer, 1990).

The origin of belief functions theory started with the works of Arthur P. Dempster. Those works are related to the statistical inference theory generalizing the Bayesian inference. G. Shafer proposed belief functions as general framework of representation of uncertainties, including the probabilities theory like particular case. Extensions to the Dempster–Shafer theory (DST) contributed to the enrichment of the belief functions theory (Bloch 2005; Bloch 1996; Denoeux 2004).

Ph. Smets suggested a model named transferable belief model (TBM) providing coherent non-probabilistic interpretation of the DST and clarifying the concept subjacent with it (Smets, 1990).

The belief functions theory is one of the theories largely used for information sources fusion considering the fact that it takes into account simultaneously sources uncertainties and provided information inaccuracy. It is reduced to the theory of probability and the theory of the possibilities in particular cases (Burrus 2003, Vannoorenberghe, 2003).

### 2.1 Information sources and power set

Each source of information being in general imperfect, it is significant to combine several sources in order to have better knowledge of the "world". We will consider in the continuation that we have *n* sources of information $S_i$ with $i \in \{1, \ldots, n\}$.

Those sources must make a decision on an observation $x$ in a whole of $k$ decisions $C_1, \cdots, C_k$. Let $\Omega = \{C_1, \cdots, C_k\}$ being the frame of discernment composed of $k$ hypotheses (exclusive and exhaustive), $2^\Omega$ is the power set (it is the set of parts of $\Omega$ ($2^\Omega = \{A_i | A_i \subseteq \Omega\}$) and the $A_i$ are the events of $2^\Omega$ with $i \in \{1, \ldots, |2^\Omega|\}$.

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### 2.2 Belief mass functions

The belief mass function $m(A)$ (or simply mass function) of an event $A$, is the confidence carried strictly in $A$ without being able to be divided onto the hypotheses composing $A$. The focal elements are the elements of $2^{\Omega}$ of non null masses. If the source is perfect, information is precise and sure, there is thus a single hypothesis $C_i$ such as $m(\{C_i\}) = 1$.
The mass functions are then defined on each subset of the set of disjunctions of $2^{\Omega}$ to values in [0,1]. The distribution of mass is written according to (1) :

$$\begin{aligned} m &: 2^{\Omega} \rightarrow [0,1] \\ A &\rightarrow m(A) \end{aligned} \quad (1)$$

Dempster proposes a conjunctive rule of combination between sources called orthogonal sum. This combination causes to assign the masses to propositions of which the number of elements is less than that of the original propositions. For two sources $S_1$ and $S_2$, one writes the orthogonal sum $\oplus$, in the following form (2):

$m = m^{S_1} \oplus m^{S_2}$, which is written for an event $A$ like:

$$m(A) = \sum_{B \cap C = A} m^{S_1}(B) \times m^{S_2}(C) \quad (2)$$

Evidential modelling makes it possible to represent at the same time the inaccuracy and uncertainty through two functions of credibility and plausibility, derived from the mass functions. The decision is done by maximization of one or the other of these two functions.

### 2.3 Transferable Belief Model

In this model, two levels can be distinguished: the credal level where the beliefs are modelled and revised, and the pignistic level in which the belief functions are transformed into probability functions, known as pignistic ($BetP$), for the decision-making (Smets, 1990).
Maximum of pignistic probability is generally considered with singletons hypothesis $C_j$ because of the additivity of probabilities. With singleton hypotheses we obtain the following equation (3):

$$BetP(C_j) = \frac{1}{1-K} \sum_{C_j \in A_i, A_i \neq \phi} \frac{m(A_i)}{|A_i|} \quad (3)$$

With $K$ is the conflict between sources expressed usually as the mass of the empty set $\phi$ like illustrated equation (4):

$$K = m(\phi) = \sum_{\substack{A \cap B = \phi \\ A \in 2^{\Omega}, B \in 2^{\Omega}}} m^{S_1}(A) \times m^{S_2}(B) \quad (4)$$

The name “Transferable Belief Model” (TBM) comes from the transfer of belief allocated initially in a proposition towards a more specific subset of it. So, the dynamic part of the TBM is related to belief revision (here belief transfer) following the awareness of new information.
The transfer of belief in the TBM satisfies the rule of conditioning of Dempster. Let $B$ an event of $2^{\Omega}$, we consider for example that we have a new information which implies that all solutions of the problem are in $B$. The conditional mass $m[B](.)$ (the hooks represent conditioning) is given by not normalized rule of conditioning of Dempster according to equations (5):

$$\begin{aligned} &if\ A \subset B \text{ and } A \neq \phi : \\ &\quad m[B](A) = \frac{1}{1 - \sum_{C \subseteq \bar{B}} m(C)} \sum_{C \subseteq \bar{B}} m(A \cup C), \\ &else\ \ (A \not\subset B \text{ or } A = \phi): \\ &\quad m[B](A) = 0 \\ &\text{and } m[B](B) = 1 \end{aligned} \quad (5)$$

### 3. PROPOSED APPROACH

The proposed classification system consists of three stages: First of all, the masses distribution calculation for each point of the image according to a classification based on spectral information, and then the beliefs transfer on the basis of contextual information (interior or external crown). Finally, a stage of fusion with the structural source of information provides a new distribution of combined masses.

### 3.1 Spectral classification based on belief functions theory

Classification by belief function theory requires, at the outset, an estimation of belief mass functions for the calculation of the resulting decision functions (credibility, plausibility or pignistic probability) on which the classification process decisions are based. We proposed in previous papers (Ben Dhiaf and all, 2007; Ben Dhiaf and all,2008-a), two methods of belief masses estimation based on grey levels histograms of learning zones. The first is a method that passes through a distribution of possibilities and the second directly reveals a belief mass estimation.

### 3.2 Integration of contextual information

In (Ben Dhiaf and all, 2008-b), we proposed a mean of conflict management by determining the subset of sources to use for each context. This approach reduces complexity since we consider, for each context, only a subset of sources validated by contextual variables. In this paper, we propose another method taking advantage of the context and allowing reducing the possible classes set for a given context.

Each context is determined according to contextual variables $z_j$ and is described by a vector that we note *Context.* Each element $\alpha_i$ of the vector *Context* is a boolean value. It expresses if the class $C_i$ is possible for this context or not. $\alpha_i$ = 1, if $C_i$ is possible in the considered context, else $\alpha_i = 0$ ($C_i$ belongs to an impossible class along with the considered context : $C_i \in \overline{Context}$ ).

Let $Z=\{z_1, z_2 \cdots, z_p\}$, the space of all the possible contexts, composed of $p$ contexts $z_j$ with $j \in \{1,\ldots,p\}$. We will describe each context with a row vector $Context = [\alpha_1 \quad \alpha_2 \quad \cdots \quad \alpha_k]$, $\alpha_i \in \{0,1\}$. The size of this vector is equal to the cardinality of the frame of discernment $\Omega$. Contexts can be written in the following form (6). Each row of the matrix corresponds to a context (determined according to contextual variables).

$$M\_contexts = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1k} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ \alpha_{p1} & \alpha_{p2} & \cdots & \alpha_{pk} \end{bmatrix} \tag{6}$$

Consider some examples of contextual variables: Altitude, Crown and Structure.

Altitude can take the values: high, average, low;

Crown can take the values: interior of a crown, exterior of a crown;

Structure can take the values: circular, rectangular, ellipsoidal.

In our application, we consider the contexts: Crown (interior of a crown) and $\overline{Crown}$ (exterior of a crown). Some classes (non forest classes) cannot belong to interior of a crown for example. The idea is then to transfer the mass associated with the impossible classes towards the possible classes.

We propose a transfer of beliefs according to the context crowns. We will call the masses obtained after beliefs transfer "contextual masses". We write the distribution of contextual masses in the following form (7) :

$$\begin{gathered} m(C_i) = x_i \\ 0 < x_i \leq 1 \text{ if } C_i \in \text{crown}\,(context) \\ \text{and} \qquad x_i = 0 \text{ if } C_i \in \overline{\text{crown}}\ (\overline{context}) \end{gathered} \tag{7}$$

### 3.3 Integration of structural information

In this section we are interested in the integration of structural information in the fusion process. The indices of forms being able to be used are varied: area, perimeter, circularity, rectangularity, ellipticity. We retain for this application the area (surface) of the crowns as structural measure.

The distribution of mass that we propose for the structural source is inspired from distances calculations. Thus we write the structural mass of a crown as illustrated by equation (8):

$$m_{crown}(C_i) = \frac{1-d_i}{D} \tag{8}$$

With $d_i$ is the normalised distance (between areas) between the considered crown and the average area of the class $C_i$ :

$$d_i = \frac{|a-a_i|}{norm} \quad \text{with } norm = \max_{i\in\{1,\ldots,k\}}(a_i) - \min_{i\in\{1,\ldots,k\}}(a_i)$$

$$D = \sum_{i\in\{1,\ldots,k\}}(d_i)$$

$a$ : Area of the considered crown,

$a_i$ : Average area of the crowns of $C_i$ ,

$\max_{i\in\{1,\ldots,k\}}(a_i)$: Maximum of the average areas of all classes,

and $\min_{i\in\{1,\ldots,k\}}(a_i)$ : Minimum of the average areas of all the classes.

In the end of the proposed classification process, we propose to combine structural information relevant to a crown (described by the structural masses distribution) with the spectral information of pixels of the same crown (described by the mass distribution after transfer of beliefs based on contextual information: contextual masses distribution).

## 4. APPLICATION

This section illustrates the application of our approach on a window of the PIR band of high resolution Quickbird satellite image of an area at the north of Tunisia (Cf. figure 1). The forest inventory corresponding to the same scene of the image emphasizes four classes: Algerian oak, cork oak, naked soil, soil with little coverage.

We propose first to explain the general principle of the algorithm of trees crowns delimitation (extraction) by Brownian motion (paragraph. 4.1). After, we present results of spectral classification based on pignistic probabilities functions maximisation. The belief masses distribution is deduced from histograms of learning areas corresponding to classes of the image (paragraph. 4.2). Revision of this masses distribution on the basis of contextual information (cf. paragraph 3.2) provides a new one (paragraph 4.3). The last step of our approach allows combining with structural information (paragraph 4.4).

Figure 1. A window of the PIR band of the QuickBird image

### 4.1 Extraction of trees crowns by Brownian motion

The trees crowns extraction algorithm by Brownian motion (ECBM) can be divided into four steps: Pretreatments, extraction of local maxima, delimitation of trees crowns and definition of borders (Erickson, 2004).
As first pre-treatment, ECBM algorithm eliminates everything that is different from tree (naked soil, rocks... etc), then it calculates the distance to the background and performs a Gaussian smoothing.
The local maxima represent the tops of the trees. ECBM algorithm determines local maxima by application of a mask on the smoothed image.

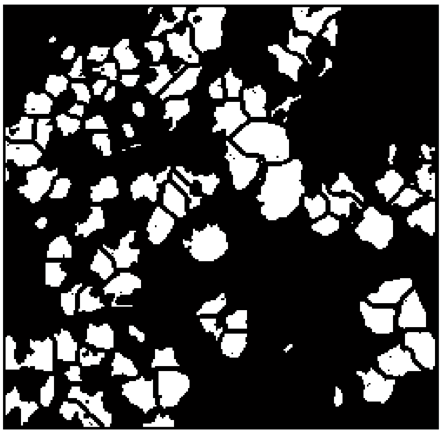


Figure 2. Extraction of trees crowns by Brownian motion algorithm

The phenomenon of the Brownian motion represents the random movement of a suspended particle in a fluid. Then, for each local maximum detected, the ECBM algorithm applies a Brownian movement to a particle initialized to the top to reach the crown of the tree. Position of the particle after N stages is equal to the sum of N random vectors of displacement of the particle. The limitation of the borders corrects the effects due to crowns overlapping. This limitation permits to obtain independent crowns ready to be classified.
The image of figure 3 is the binary image resulting of the application of the ECBM algorithm on the image of figure 1. Figure 3 illustrates the efficiency of this algorithm by superposing the limits of the detected crowns on the image of figure 1.

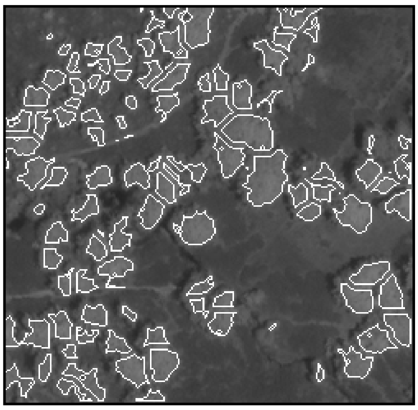
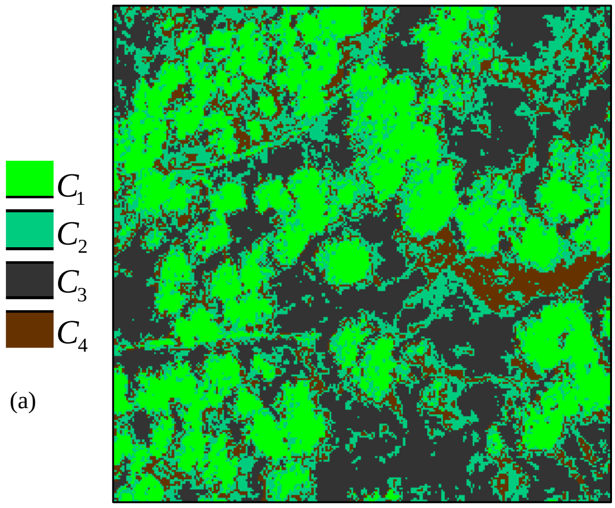


Figure 3. Result of matching of the Quickbird image window and the corresponding image of crowns

### 4.2 Spectral classification

Figure 4 illustrates the result of the image classification while being based on the maximum of the masses estimated on the basis of supervised training (Ben Dhiaf and all, 2007; Ben Dhiaf and all,2008-a),.

This result reveals a great confusion between forest and non forest species. Although the value of Kappa coefficient (0.81) and the mean of the values of confusion matrix diagonal (85.92) shows that our spectral classification isn't bad, a confusion essentially between class 2 is and the other classes 1 and 3 (cf. Table 5) needs to be reduced.




(b)

Figure 4. (a) : Legend of classes, (b) : Spectral classification based on maximization of pignistic probabilities functions.

| | C1 | C2 | C3 | C4 |
|---|---|---|---|---|
| C1 | 92.00 | 8.00 | 0.00 | 0.00 |
| C2 | 10.91 | 60.00 | 21.82 | 7.27 |
| C3 | 0.00 | 3.28 | 96.72 | 0.00 |
| C4 | 0.00 | 5.05 | 0.00 | 94.95 |

Table 5. Confusion matrix of the spectral classification

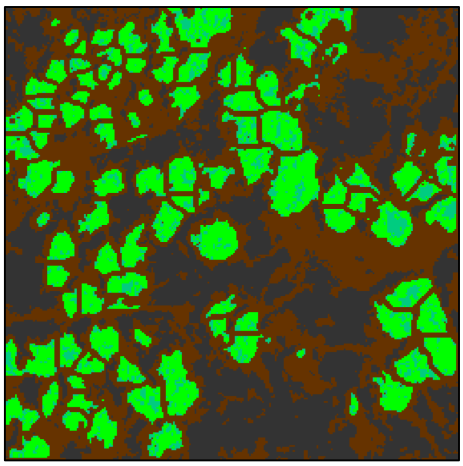


Figure 6: Result of classification after revision

### 4.3 Transfer of beliefs and new classification

Figure 7 illustrates the result of belief transfer applied on the basis of contextual information on the spectral mass distribution. We note that this transfer reduces considerably the presence of forest species pixels in classes $C_3$ and $C_4$ and concentrated the presence of the classes $C_1$ and $C_2$ in interior pixels of the trees crowns. At this step, the classification of figure 4 still leaves a great confusion between the two classes $C_1$ and $C_2$.

### 4.4 Fusion with structural information

Figure 8 shows the relevance of the integration of structural information (surface of the crowns). Indeed the figure shows a better distinction between the classes $C_1$ and $C_2$ in comparison with figure 3 and 4.

The following step consists on unification of classes assigned to pixels belonging to the same tree crown. The result shown in figure 8 converges to the field reality (comparison made relatively to the forest inventory and after discussion with the experts of the ministry for agriculture of Tunisia-direction of the forests). Table 9 presents an evaluation of tree crowns classification. The percentage of well classified tree crowns is satisfactory (94% for C1 and 88% for C2).

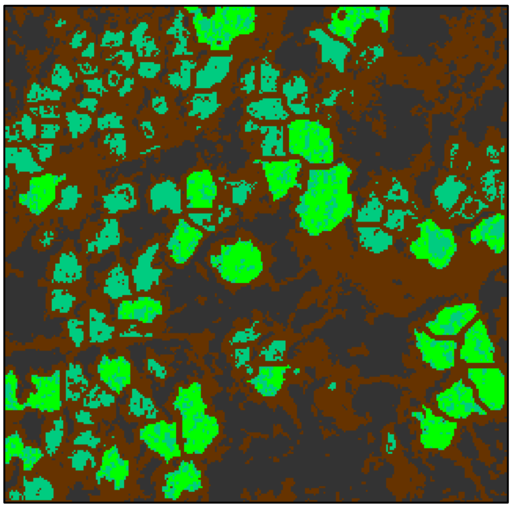


Figure 7: Classification after fusion with structural information

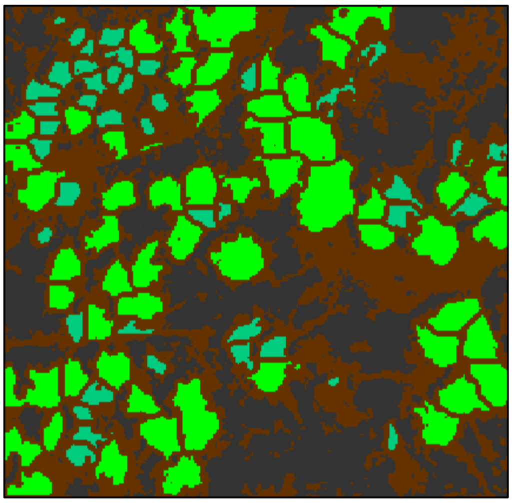


Figure 8: Classification after revision, combination and unifying the interior of crowns

| | C1 | C2 |
|---|---|---|
| Tree crowns number | 57 | 43 |
| Misclassified crowns number | 3 | 5 |
| Well classified crowns number | 54 | 38 |
| Percentage of well classified crowns | 94% | 88% |

Table 9: Evaluation of tree crowns classification

## 5. CONCLUSION

We presented in this paper an approach which makes it possible to integrate contextual information for the transfer of belief dedicated to the classification of the forest images. The taking into account of the context and expert knowledge in the revision of the masses enabled us to manage the conflict between the forest species. The results confirm well the importance of this choice. The advantage of this approach brings a double advantage: Separability between the forest species and a reduction of calculations complexity of the belief masses since contextual information enables us to filter combinations of classes not validated by the contextual assumptions.

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