Detection of Hedges in a Rural Landscape Using a Local Orientation Feature: From Linear Opening to Path Opening

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Abstract—The detection of hedges is addressed in this paper. A hierarchical detection scheme in two steps is proposed. It is based on the use of both spatial information and spectral information in the detection process. First, woody elements are detected using the spectral information. From the membership map, the local orientation of each pixel is computed using directional filters. The morphological directional profile is defined as the composition of the outputs of directional filters with a varying orientation parameter. The local orientation feature is defined as the difference between the maximum and the minimum values of the morphological directional profile. A second detection step is done using the local orientation feature and the membership value to the woody elements class to extract the hedges. Experiments conducted on several real satellite images show that the method provides very good results in terms of detection accuracies. For one experiment, the overall accuracy is increased 80% to 91% with the proposed method. Furthermore, the methods is robust even if the size of the training samples is limited.

Index Terms—Detection, directional morphological filters, hedges, local orientation, path opening, support vector data description, very high spatial resolution image.

I. INTRODUCTION

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ANDSCAPE ecology focuses on the study of spatial patterns and process relationships [1]. In particular, researchers in that field try to model how configuration and composition of landscapes are related to ecological processes [2]. To that end, accurate identification and characterization of the landscape patterns present (agricultural fields, man made objects, water, etc.) are key issues.

In agricultural landscapes, it is widely recognized that features such as “tree outside forest” (hedges, copses, scattered trees, small remnant woodlots, etc.) play an important role for the conservation and restoration of biodiversity [3]. These green veining elements are used as refuge, reproduction or corridor habitats for various species [4]. Hedgerows ensure various other functions such as physical, chemical and biological fluxes control (water protection, erosion control), windbreak, and barrier [5]. These semi-natural elements are essential in the agricultural landscapes. They are the main components of the green infrastructure plans defined for conservation planning from the local to the global (statewide) scale [6]. For instance in France, one conclusion of the “environment round table” is the need of a cartography of the “green belt network” (or green infrastructures) [7]. Another example is given by the European Union which conditions its funding to farmers based on how they maintain hedges inside their farms [8].

In the past, small and linear woody elements were mapped manually, by visual interpretation of aerial photographs, or by traditional field-based recognition. Obviously, this approach was highly time consuming and not appropriate for large areas. Besides, the small green veining objects were not always included in the spatial databases produced by the National Mapping Agencies, or not distinguished by category [9]. In addition, when this is the case, their cartographic representation does not necessarily fit the user needs because green veining objects like hedgerows are very application dependent [5]. For instance, the useful minimum length to define a linear object as a hedge may differ according to the species studied and its dispersion ability.

In recent years, the extraction of hedgerows from remotely sensed images has received much attention. Remote sensing offers a good solution for an automatic extraction of hedges over large areas with an adequate temporal periodicity. From sensors with a finer spatial resolution (very high spatial resolution sensor—VHR sensor), such as SPOT-5 or WORLDVIEW, hedges are visually identifiable. However, making the extraction of hedges automatic or semi-automatic is a difficult task because (i) spatially a hedge is a linear object similar to a road or a path and (ii) spectrally it is very similar to woody vegetation like forests. Its local contrast with the surrounding objects can also make the detection more complicate as well as its position. For instance, hedges are usually located along roads or connected to forest patches.

Recent methods in the remote sensing literature tackle the problems above by combining both spatial and spectral information in the mapping process. Traditionally, these methods con-
sider a hedge as a linear object made of woody elements. The length of the hedge is in general defined according to the length parameter of the spatial processing approach used to extract the spatial information. These approaches can be roughly divided into four categories:

1) **Pixel based approaches**: Spatial and spectral features are extracted from the image. Principal component analysis or normalized difference vegetation index are most often used to extract spectral features, while textural information such as standard deviation or entropy are computed to determine the spatial features [10]. Then a detection/classification step is performed to extract the hedges at a pixel level. The main problem of such approaches is that with VHR sensors, the spectral information is not sufficient for detecting the hedges accurately and the extracted spatial information is usually isotropic, i.e., it is identical for an oriented spatial object and for an un-oriented spatial object.

2) **Objects based approaches**: The image is first segmented to extract spatial objects and features are computed on the extracted objects. Then a detection/classification is used to extract the hedges at an object level [11], [12]. However, the segmentation step is difficult for a VHR image and over/under segmentation leads to poor detection results in terms of accuracy.

3) **Multiscale approaches**: A multiscale analysis in the image domain is first performed. Then spatial and spectral features are extracted. These approaches can be seen as a compromise between pixel based and object based approaches. In [13] and [14] two methods were proposed based on the eCognition software. However, in those papers several parameters for the multiscale segmentation and for the detection usually have to be tuned, which makes such methods difficult to used in practical situation, especially when the area to process is large.

4) **Local approaches**: These methods attempt to find predefined objects in the image. For instance, templates matching [15], Markov random field [16] or hit or miss transform [17] are popular approaches. Nevertheless, whatever methods are selected, a template (or a statistical model or a structuring element) needs to be defined. In general, the template has a fixed size, shape and orientation and thus a large set of templates must be tested for the detection, which consequently limits the effectiveness of such methods.

Alternatively, a multi-step classifier has been proposed in [8]. The multiple classifier detects woody elements based on a spectral feature—the normalized difference vegetation index (NDVI)—and spatial features (texture and size) then followed by a spatial processing which extract hedges from all the woody elements. In particular, Aksoy and co-workers used a range of Gabor filters to extract information about the texture at different scales and the size of the objects were analyzed using morphological granulometry [8]. In particular they used isotropic filters, which apply equally in all directions. By using those filters, they were not able to discriminate between forest and hedges because these objects share the same textural and spectral characteristics. Therefore, the authors used a post processing step to extract linear woody objects from all the woody elements.

In this work, we propose to apply directional morphological filters [18], [19] for the detection of hedges. Directional filters allow the processing of an image in a defined direction. Hence, it is possible to preserve or remove objects according to their orientations and also enable the discrimination of objects with different orientations in the image from objects with no main orientation. This property is very important for the discrimination of the hedges from the other woody structures.

Filters by reconstruction [20] and path filters [21] are investigated in this article for the detection of hedges. Filters by reconstruction use a linear structuring element of a given size and orientation, while path filters use a path of a given size and orientation as a structuring element. A path differs from a linear structuring element in the way that it is not necessarily perfectly straight [22], [23] and it can fit better the shape of hedges than a linear structuring element. Following [24], [25], these filters are applied to compute the morphological directional profile, i.e., the result of the filtering for different orientations. Then the local orientation feature is defined from the directional profile.

When spatial and spectral features have been extracted, several strategies can be used to combine them [26]. Features can be stacked into a single feature vector and used as an input to a detection algorithm (feature fusion) [27]. Or several independent detectors can be applied to each feature and then fused each decision rules (decision fusion) [28]. Feature fusion is widely developed in remote sensing because of its simple implementation. For instance, [8] and [12] used this approach. But feature fusion can lead to large feature vector with redundant features [27]. In this work, an intermediate scheme is discussed: a hierarchical method that includes both decision fusion and feature fusion. The proposed approach is motivated by the fact that discriminating between woody elements and non-woody elements is easy when only spectral and textural features are used but the discrimination becomes harder when additional spatial features are included. Conversely detecting hedges is complex when the whole image is considered but becomes simpler when candidate pixels are restricted to woody elements. Hence, it is proposed to first perform a detection of the woody elements, without making any decision, then compute the local orientation on the membership image and finally perform a second detection for the hedges using the local orientation feature and the output of the first detector (see Fig. 1 for a flowchart of the method). Feature fusion is applied in the second individual detector and decision fusion is done between the first and the second detector. The original problem that is difficult is cut into two simpler problems, i.e., to detect woody elements in the image and then detect hedges in the woody elements.

The last element of the proposed method is the detection algorithm. Here, the choice has been driven by practical considerations. In a real case scenario, it is difficult to sample all the different thematic classes that are present in the image. Therefore, a detection algorithm that concentrates on the class of interest is much simpler to use since only a few samples of the class of interest need to be labeled. In [29], two generative approaches
were used. They were based on a binary quadratic discriminant detector [30, ch. 4.3]. Two a priori distribution were used to approximate the distribution of the class of interest: a Gaussian distribution and a mixture of Gaussian distributions. The latter can handle multimodal distribution for the classes. When the full set of features is used, no difference in terms of classification accuracies is found between the two detectors. One conclusion in [29] is that the hedges class is well approximated by a single Gaussian distribution. However, the authors have used a very large training set (about 500,000 pixels) which is difficult to obtain in practice. The results obtained with a smaller training set might be worst, since the distribution would be less well estimated. In this work, rather than fixing an a priori distribution on the data, the support of the distribution is assumed to be bounded. The pattern recognition problem is, therefore, simplified, since rather than the full estimation of a distribution, only its support needs to be estimated. Once the support is estimated, the detection is done by checking if a given sample belongs or does not belong to the support. The support vector data description algorithm (SVDD) is used to estimate the support of the class of interest in the space [31]. SVDD is known to perform well in detecting a particular class of interest in remotely sensed image analysis [32] and requires in general a smaller training set than conventional parametric method.

The rest of the paper is organized as follows. In Section II, the data are presented. Then, directional filters and the local orientation are described in Section III. The SVDD is detailed in Section IV. Experimental results are given and discussed in Section V. Section VI comes out with conclusion and perspectives.

II. STUDY SITE AND MATERIAL

The study site is included in the territory of the Long-Term Ecological Research (LTER-Europe) study site Valleys and Hills of Gascogne, France (43°13′N, 0°52′E). It is a farmland typical of south-western France (agricultural mosaic with wooded patches) with mixed production systems.

A Worldview-2 multispectral image has been used in the experiments. The image has been acquired on September 20, 2011. It has four spectral bands (450–510 nm, 510–580 nm, 630–690 nm and 770–895 nm) with a spatial resolution of 1.8 meter by pixel. The original size is 6909×3697 pixels.

Fig. 2. (a)–(c) False color images of the extracted subscenes. (d)–(f) Corresponding reference data. Yellow pixels correspond to hedges pixels, blue pixels correspond to forest pixels, green pixels correspond to non-woody pixels and black pixels correspond to unlabeled pixels.

### TABLE I

<table>
<thead>
<tr>
<th></th>
<th>Image 1</th>
<th>Image 2</th>
<th>Image 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedge</td>
<td>1,102</td>
<td>1,001</td>
<td>1,115</td>
</tr>
<tr>
<td>Forest</td>
<td>306</td>
<td>551</td>
<td>362</td>
</tr>
<tr>
<td>Non-woody</td>
<td>1,339</td>
<td>878</td>
<td>1,112</td>
</tr>
<tr>
<td>Total</td>
<td>2,747</td>
<td>2,430</td>
<td>2,589</td>
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</table>

Three subscenes of 400×400 pixels have been extracted for the experiments, they are displayed in Fig. 2. Training and test sets have been constructed manually from the image. These sets are made of hedge, forest and non-woody pixels. The overall set of labeled pixels are displayed in Fig. 2. The number of labeled samples for each image is reported in Table I.

III. LOCAL ORIENTATION

This section is dedicated to the definition of the local orientation feature. First, two directional morphological filters are presented: the opening by reconstruction with a linear structuring element and the path opening [19]. Then, the morphological directional profile (MDP) is detailed along with the local orientation.
A. Directional Morphological Filters

For simplicity, only opening filters are discussed. But readers should be aware that dual operators exist, i.e., closings, which act similarly on the dark objects of the image [18]. Morphological operators analyze spatial relationship between pixels using a set of known shapes and sizes, called the structuring element (SE). This SE can be a rigid set of pixels, e.g., a line of size 9 pixels and 45° of orientation, or it can be an adaptive shape, e.g., a path between two pixels. The two fundamental operators in mathematical morphology are erosion and dilation [18]. These operators are applied to an image with a given SE. To erode an image consists of finding where the SE fits the objects in the image. The dilation, which is dual to the erosion, shows where the SE hits the objects. Many morphological operators are based on the combinations of erosion and dilation. An overview of operators can be found in [18]. Using a linear SE, it is possible to define directional morphological filters, such as the opening operators which is discussed in the following.

1) Opening by Reconstruction: The opening removes all the bright objects of the images which do not contain the structuring element. It is an anti-extensive filter, i.e., the value of a transformed pixel is less than or equal to the value of the original pixel. Typically, values of pixels belonging to a removed object are changed to lower values, which are given by the first object that contains both the structuring element and the original object. Fig. 3 presents a synthetic illustration of opening by reconstruction and of the anti-extensivity property.

The anti-extensivity property is very important in the application discussed here. When using the opening by reconstruction with a linear SE, a pixel whose value has been reduced necessarily belongs to an object that does not contain the SE. Conversely, if the value of the pixel does not change, it means that the SE fits the object to which the pixel belongs to. Hence, by varying the orientation parameter it is possible to assess the orientation of the objects. Fig. 4 shows example of opening by reconstruction with a linear SE and different orientation. According to the orientation of the SE, the hedge is preserved or removed from the image.

However, the hedge considered in Fig. 4 is straight which is not always true for hedges. Hedges may be slightly curved, therefore, a linear SE is too restrictive for an accurate spatial characterization of hedges. Consequently, a more flexible SE must be used. In the following, path openings are presented as a more flexible filters for the characterization of hedges.

2) Path Opening: Path opening removes pixels that are not connected by a path of a given length and orientation. While a linear opening works with a fixed SE, the path opening allow for more flexibility, allowing the pixels to be connected following a flexible line rather than a straight line [21], [22]. A path between two pixels is based on the notion of adjacency. The adjacency defines the orientation in which successors will be added to the path, see Fig. 5 for an illustration of adjacency as a function of the orientation. The four different orientations allow to assess the orientation of hedges inside a 90° cone.

A path of size L of orientation θ is defined as the set of L adjacent pixels. Fig. 6 shows an example of paths for θ = 0°. The black pixels are connected in the given orientation and several paths of different length can be identified. The three different paths that can be found are of length 2, Fig. 6(a), 5, Fig. 6(b), and 6, Fig. 6(c). These paths are of maximal length because no black pixels can be added to these paths in the given orientation. A path opening of size 6 removes all the pixels that do not belong to a path of size 6 or greater, Fig. 6(d). If a linear opening with an horizontal SE of length 6 is applied on the same original image, all the pixels would be removed because the SE cannot connect any two pixels. This example shows the flexibility of the path opening algorithm and how it helps in the detection of hedges which are mostly linear shapes within a given orientation.

The path opening was computed using the DIPlib Matlab library (http://www.diplib.org/).

B. Morphological Directional Profile

The morphological directional profile (MDP) is defined as the composition of directional filters outputs with a varying orientation parameter. It is typically built with openings and closings.
the local orientation by reconstruction with a linear SE or path opening. Thanks to the anti-extensivity property of the opening operators, the MDP provides information about the orientation of the object. The anti-extensivity property means that the gray level of a pixel after the filtering is less than or equal to its original value. Hence, for a given orientation parameter, if the gray level of a pixel does not change, then the pixel belongs to an object where it is possible to fit a SE/path of size L and orientation θ. Otherwise, i.e., the gray level decreased, then the pixel belongs to an object where it is not possible to fit the SE/path.

Fig. 7 presents two MDPs build with either opening by reconstruction or path opening for a pixel corresponding to a hedge and for a pixel that does not correspond to a hedge. From the figure, a MDP that corresponds to a hedge is curved since the output of the directional filter changes a lot in function of the given orientation. Conversely, a MDP that does not correspond to a hedge is almost flat since the output of the directional filter is the same whatever the orientation.

It is possible to derive local spatial feature from the MDP [25]. In particular, for a given pixel x the local orientation LO(x) is defined as the difference between the maximum value and the minimum value of the MDP:

\[ LO(x) = \max_{\theta} \{ MDP(x) \} - \min_{\theta} \{ MDP(x) \} . \] (1)

From Fig. 7, it is clear that if the pixel belongs to a hedge (or any oriented bright object) the local orientation feature will have a high value. On the contrary, when the pixel belongs to a non-oriented object (e.g., a meadow or a forest) the local orientation feature will have a very low value.

**IV. SUPPORT VECTOR DATA DESCRIPTION**

In this paper, a non-parametric detection algorithm has been selected to detect hedges. This choice has been motivated by two reasons:

1) If a multiclass classification algorithm is applied for the detection of hedges, the class corresponding to hedges can be extracted after the classification process. However, multiclass algorithms require training samples for each class of the image in order to perform accurately. In a real scenario, it is difficult to identify all the classes in the image, especially when a large area is covered, and it can be even more complicated to get a sufficient number of pixels for each class. Detection of a specific class is a more realistic approach when only a single class is of interest. In that case, it is only necessary to sample correctly the class of interest.

2) Parametric detection methods require the definition of density distribution for the class of interest. For samples that combine both spectral and spatial features, such a definition can be difficult. Furthermore, the hedges-class is made of several woody species which can lead to a multimodal distribution. Similarly, the negative class might be difficult to model since it is made of several different objects. Therefore, a non-parametric method might be more appropriate [30, ch. 10.3].

In this work, the support vector data description (SVDD) algorithm is used for the detection of hedges. SVDD is a kernel method, which is non-linear and non-parametric [34, ch. 8]. It estimates the support of a set of samples by computing the minimum volume enclosing hypersphere that contains the training pixels. Using kernel function $k$, the hypersphere is implicitly computed in a feature space associated with the kernel function. Furthermore, it is possible to add “negative” training pixels
Fig. 8. Influence of the regularization parameter of the SVDD. The SVDD was trained with (a) only positive samples and \( C = 1 \), (b) only positive samples and \( C = 0.1 \), (c) positive and negative samples and \( C = 1 \) and (d) positive and negative samples and \( C = 0.1 \). The red triangles are the positive samples and the blue squares are the negative ones. The black line is the decision boundary found with SVDD and the black cross are the samples inside the optimal hypersphere.

(pixels that should not be included in the hypersphere). In comparison to multiclass algorithms, the negative class does not need to be fully sampled [31]. If negative samples are available, they can be used in the training process to get a better decision boundary. If not, the algorithm can still be trained but worse detection results can be expected [31].

Up to now, in remote sensing application the SVDD has usually been trained with positive training samples only, see for instance [32].

Let \( S = \{ (x_i, y_i) \}_{i=1}^n \) be the training set, with \( x_i \in \mathbb{R}^d \) and \( y_i = 1 \) if \( x_i \) is a positive sample and \( y_i = -1 \) if it is a negative sample. The optimal hypersphere parameters \( \beta_i, i \in \{1, \ldots, n\} \), are found by solving the following optimization problem (for details, see [31] and [35]):

\[
\max_{\beta_i} G(\beta) = \sum_{i=1}^n \beta_i y_i k(x_i, x_i) - \sum_{i=1}^n \sum_{j=1}^n \beta_i \beta_j y_i y_j k(x_i, x_j)
\]

with \( C \geq \beta_i \geq 0 \) and \( \sum_{i=1}^n \beta_i y_i = 1 \).  
(2)

where \( C \) is a regularization parameter such as \( 0 < C \leq 1 \) that penalizes the errors\(^1\) during the optimization. When \( C = 1 \), no errors are allowed during the optimization process, while low values of \( C \) results in allowing errors for a fraction of positive and negative samples. The square value \( R^2 \) of the radius of the hypersphere is given by \( G(\beta) \): The square Euclidean distance \( d_C \) to the center \( C \) of the hypersphere for a sample \( x \) is given by

\[
d_C(z) = k(z, z) + \sum_{i=1}^n \beta_i \beta_j y_i y_j k(x_i, x_j) - 2 \sum_{i=1}^n \beta_i y_i k(z, y_i).
\]

The detection is done by evaluating if the distance is greater (negative class) or smaller (positive class) than \( d_C \). It is also possible to convert the distance to a “probability-like” value using Platt algorithm [36]:

\[
p(y = 1 | z) = \frac{1}{1 + \exp(\gamma_1 d_C(z) + \gamma_2)}
\]

where \( \gamma_{1,2} \in \mathbb{R} \) are found by optimizing a regularized likelihood function [36]. Turning distance to probability is convenient in our application since the opening operators act on bright objects. After the woody/non-woody detection, outputs of the SVDD are converted to probabilities to ensure the brightness of woody elements and to bound the dynamic of the SVDD output between 0 and 1.

The choice of an appropriate kernel is an important issue. An ideal kernel would map the data into a spherically shaped area (or at least a bounded region) in the feature space [31]. Among the large choice of kernel function [37], some of them satisfy the previous condition. The feature vectors associated to the conventional Gaussian kernel are unit norm vectors and hence this kernel satisfy the previous condition. The kernel is expressed as follows:

\[
k(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|^2}{2\sigma^2}\right).
\]

The hyperparameter \( \sigma \) is selected as the average Euclidean distance among the positive training samples:

\[
\sigma^2 = \frac{2}{(n_+ - 1)(n_+ - 2)} \sum_{i=1}^{n_+} \sum_{j=i+1}^{n_+} |x_i - x_j|^2
\]

where \( n_+ \) is the number of positive samples.

A synthetic example of SVDD is given in Fig. 8. The samples were uniformly drawn between [0,4] x [0,4] and positive samples \( y = 1 \) correspond to samples that fulfill \( |x|^2 < 5 \) or \( |x|^2 > 20 \). The SVDD was trained with either positive samples only or positive and negative samples. The hyperparameter \( \sigma \) was tuned according to (6). From the figures, it is clearly seen that using both positive and negative samples improves the detection. In Fig. 8(a) and (b), the support of red samples is not correctly estimated. The support is estimated as mono-modal while it is multi-modal. Adding negative examples helps the SVDD to find the right support of the data. As expected, low value of \( C \) value leads to a smoother decision boundary with a fraction of samples wrongly detected while high value constrains the detector to learn almost perfectly the data, which can results in overfitting.

For real data, a compromise must be done to simultaneously learn correctly the data support and have a good generalization ability. According to the constraint in (2), the number of errors (positive or negative samples that are wrongly detected during the training process) is bounded by \( 1/C \) [31]. After several experiments, for the first SVDD, the number of errors is set to be equal to or less than 10% of the total number of training samples \( (C \approx 1/0.1n) \). For the second SVDD, the bound on
the number of errors is larger and set to approximately 35% \((C \approx 1/0.35n)\). Being “strict” (few errors are allowed) in the first SVDD is necessary to avoid non-woody vegetation to be detected as woody element.

Finally, it is important to note that SVDD with positive and negative samples concentrates on the estimation of the support in the feature space of the positive samples. Hence, the decision boundary obtained with SVDD is different from the decision boundary that might be obtained with a two-class classifier, for instance a SVM trained with the same training samples, that concentrates on separating the samples.

V. EXPERIMENTAL RESULTS

A. Experimental Settings

For all experiments, half of the pixels in each class is used for learning, the other half is used to validate the results via several index such as accuracy, the True Positive Rate (TPR) and the True Negative Rate (TNR). The TPR is computed as the number of positive test pixels well classified divided by the total number of positive test pixels, and represents the percentage of hedge pixels that were well detected in the test set. In the same way, the TNR is computed as the number of negative test pixels well classified divided by the total number of negative test pixels, and represents the percentage of non-hedge pixels that were not detected as hedges in the test set. The accuracy is computed as the number of correctly classified test pixels divided by the number of test pixels and represents the percentage of the test pixels that were classified correctly by the algorithm as hedge or non-hedge. For each criteria, 1 is the best value while 0 is the worst.

Each reported results are repeated twenty times, randomly selecting the pixels for the learning and for the test each time. Twenty different random pixels sets were stored to be able to reproduce the SVDD in the exact same conditions when the features are changed, using the same pixels sets. For each of the twenty results, the TPR, the TNR and the accuracy are computed. The mean and variance are also given in the following tables. Finally, the values of the hyperparameter \(\sigma\) and \(C\) are tuned according to the discussion in Section IV.

On the binary result map of the hedge detection, a post processing was applied using alternate sequential area filters \([18]\). The size of these filters was from 2 pixels to 4, beginning with an area opening. This post processing was made to eliminate isolated small groups of pixels that could not be hedges because of their small area, or small holes in hedges. The addition of this step does not give significant accuracy improvement but give a cleaner hedge map.

B. Detection of Woody Elements

Two features were compared for this problem: the original multispectral images and the NDVI (Normalized Difference Vegetation Index) images. The NDVI is a classical spectral index which have a good sensitivity to changes in vegetation cover. The photosynthetically active vegetation, such as trees and fields, has a high NDVI value whereas non-vegetation elements such as roads, sand or water and photosynthetically inactive vegetation get a low NDVI value. This index is computed using the red and the near infrared bands and vary between 1 and 1 \([38], [39]\).

The results of the detection are reported in Table II. In the table, the NDVI stands out as the better feature for the detection of woody elements, giving better results in terms of accuracy and less variance. It can be seen in Table II that the main drawback of the multispectral feature is its low TNR value (0.645) compared to the NDVI TNR value (0.892), which means a lot of negative pixels are misclassified as positive. Several non-woody elements such as fields and hedge’s shadow are often seen as woody elements in the classification because they have almost the same intensity as hedges in most of the different spectral bands. With the NDVI as a feature, the SVDD is able to distinguish some of these elements which are not photosynthetically active from the woody elements. Some fields with a high NDVI value can however remain problematic as shown in the following sections.

The NDVI will be kept as the only feature for the first SVDD from now on.

C. Proposed Method With Local Orientation

The detection is done using the local orientation. The flowchart of the method is given in Fig. 1. Two different filters to compute the local orientation were investigated: linear openings and path openings. Several lengths for the opening algorithm were also tested. The results are given in Table III for the first image, Table IV for the second, and Table V for the third. In these tables, LO and PO stand for the proposed hierarchical method. The feature for the first SVDD is the NDVI, and the features for the second SVDD are the probability map and the local orientation computed with linear openings (LO) or path opening (PO). Multispectral and NDVI stand for the detection of hedges using the spectral information only, i.e., the spectral band on one hand and the NDVI on the other.

The results report that the drawback of the linear opening feature is the low TNR value of the detection, resulting in a lower accuracy. For example on the first image, Table III, the best results with linear opening are a TNR of 0.782 and a TPR
Before including the spatial feature in the approach, a single SVDD using only the spectral features was tested. The results are reported for each image in the bottom two lines of each table. For the first image, the results show an accuracy of 67.3% for the multispectral feature alone. With the spatial feature, the results are improved: an accuracy of 81.8% was computed for the best result with linear opening, and 91.1% for the best result with path opening. It can be seen that adding a spatial feature computed with linear opening to the NDVI feature does not improve the accuracy significantly. The NDVI feature alone already gives a high TPR value. Therefore it is necessary to increase the TNR value to improve the detection. As shown above, the TNR value is the strength of the path opening feature, but the drawback of the linear opening feature.

On the third image, the proposed method using the linear opening is less accurate than using the NDVI only. For that image, the local orientation computed combined with the linear opening is not accurate.

D. Visual Analysis of the Hedge Map

In this section, a qualitative analysis of the results is presented. Looking at the hedge maps, some problematic elements can be identified. It can be seen in Fig. 9(d) that some linear features such as trenches or paths belonging to grassland with a high NDVI value can be detected as hedges. For example the beginning of a trench is partially detected as a hedge at the right of the field at the bottom of the picture. It is also interesting to notice on the probability map, Fig. 9(b), and on the local orientation, Fig. 9(c), that the field at the bottom of the picture is the most problematic area since it has a lot of linear features in it, combined with its high NDVI value. These features are not classified as hedges with path openings because they are too short, however the linear openings with a small SE detect these features as hedges. This illustration also shows that the local orientation feature is really good to eliminate forests, even when the are connected to some hedges.

Fig. 9(d) shows that some really thin hedges are not detected. The length given to the algorithm could be reduced to detect those hedges. However this would leads to the detection of more non-hedges linear features. The length given to the algorithm, therefore, depends on the purpose of the detection, a greater length will detect longer hedges and miss some short hedges, whereas a shorter length will detect most of the hedges but also non-hedges features.

The final results for the images 2 and 3 are shown in Figs. 10 and 11 with a length of 20 for the path opening algorithm.

The second image illustrate the problem of forests with peculiar shapes, and close to hedges. The detection result in Fig. 10(c) shows that hedges are successfully detected even when close to forests. However, some parts of the forests are detected as hedges when the trees are too scattered—creating some linear shapes inside the forest—as in the northern part of the large forest in the middle of the picture.

On the third image, Fig. 11(c), the detection is once again disturbed by the field with a very high NDVI at the bottom of the picture. This field being almost connected to the hedge at the bottom of the picture, the path opening algorithm see them as connected and therefore with no local orientation, missing this hedge. At the top of the picture, scattered trees at the eastern border of the forest are also detected as hedges. This picture also shows that discontinuous hedges are problematic since the path opening algorithm may fail to find a path of the required
length in a discontinuous feature, as in the hedge touching the left border of the picture.

However, aside from the peculiar features described above, the local orientation is able to successfully distinguish the hedges from the rest of the woody vegetation in all three images. The result of the detection using only the NDVI as a feature is shown in Figs. 10(b) and 11(b). These figures show that the NDVI alone detects all the vegetation as hedges, especially the forests and the cultivated fields. Another thing to notice is that some small hedges are not well detected by the NDVI alone. Adding the local orientation allows the detection of these hedges with more accuracy.

E. Influence of the Size of the Training Set

To estimate the influence of the size of the training set on the algorithm performances, an experiment was made reducing the size of the learning set. The results are reported in Fig. 12. In the previous section, half of the reference data was used for the learning of each SVDD, which represents 50% of the reference data, and the other half was used for the testing. For this experiment, the reference data was still split into two parts, but the percentage of the reference data used for the learning was reduced gradually down from 50% to 1% of the reference data, while the other 50% were totally used for testing. It can be seen that the three criteria remains high down to 10% of the reference data. When the percentage is lowered under that threshold, the value of the criteria begins to fall down, the TPR being the first one to decrease.

This shows that using only 10% of the current reference data, which would represent around a hundred of hedge pixels, 30 to 40 forest pixels and a hundred of non woody pixels, the results of the detection remains good. Hence, a limited human intervention is sufficient to make the algorithm work.

VI. CONCLUSION AND PERSPECTIVES

Detection of hedges in rural environment has been addressed in this paper. Two contributions were proposed, the local orientation and the detection with SVDD. Using morphological filters, the linear opening and the path opening, a local orientation is defined per pixel as the difference between the maximum and the minimum output value of the morphological directional profile. From the experimental results it can be observed that the path opening is a more appropriate filter for computing such spatial feature. Paths are more flexible than conventional structuring elements and thus better fit the shapes of natural hedges, which are not perfectly straight.

The SVDD provides good detection accuracies even if the size of the training set is limited. The possibility of adding “negative” samples without fully sampling the “negative” class makes the definition of the reference data easier than with a conventional statistical detection algorithm. In this work, a Gaussian kernel is used and experimental results shows that it performs well for the detection task.

Qualitative and quantitative analysis of the results on three different images shows that the use of the local orientation clearly improves the detection of the hedges. Using the spectral
information only, woody elements can be extracted correctly but hedges are difficult to extract accurately. The proposed method shows a very good TNR and a lower TPR, meaning that some hedges are missing in the final hedge map.

In this work, only spectral and orientation feature were used for the detection. Obviously, more features such as local texture or shape features can be used to improve the detection of hedges. Current research concern the definition of new features that improve the detection of the hedges. Morphological attribute filters [40] will be investigated in the future.

In this paper, it has been shown that the proposed method is robust to the size of the training set. Furthermore, adding more samples does not result in an increase of the accuracy. A more suitable strategy for building the training set would be to start with a reduced training set and use an active learning strategy to effectively build a training set that helps in detecting difficult samples correctly [41].

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