Vineyard segmentation from satellite imagery using machine learning

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Abstract. Steep slope vineyards are a complex scenario for the development of ground robots due to the harsh terrain conditions and unstable localization systems. Automate vineyard tasks (like monitoring, pruning, spraying, and harvesting) requires advanced robotic path planning approaches. These approaches usually resort to Simultaneous Localization and Mapping (SLAM) techniques to acquire environment information, which requires previous navigation of the robot through the entire vineyard. The analysis of satellite or aerial images could represent an alternative to SLAM techniques, to build the first version of occupation grid map (needed by robots). The state of the art for aerial vineyard images analysis is limited to flat vineyards with straight vine's row. This work considers a machine learning based approach (SVM classifier with Local Binary Pattern (LBP) based descriptor) to perform the vineyard segmentation from public satellite imagery. In the experiments with a dataset of satellite images from vineyards of Douro region, the proposed method achieved accuracy over 90%.

Keywords: vineyard · satellite images · machine learning · agricultural robotics · path planning

1 Introduction

The steep slope vineyards placed in the Douro Demarcated region (Portugal), UNESCO Heritage place, presents unique characteristics, which includes a number of robotic challenges. These challenges need to be overcomed so as to obtain a fully autonomous navigation system. Its unique characteristics present challenges in diverse robotic areas such as visual perception, localization, environmental modelling, control or decision making. An accurate map and localization system is crucial for safe autonomous navigation on the vineyard. However, Global Navigation Satellite Systems (GNSS) are not reliable, since the signal is constantly blocked by the hills. Dead reckoning sensors are also affected by harsh terrain conditions. Thus, VineSLAM algorithm [3] was proposed in the previous work. VineSLAM is a GNSS-freebase localization and mapping system for steep slope vineyard. This algrithm is based on the detection of natural features like trunks, performed with ViTruDe (Vineyard Trunks Detector), a tool to detect natural features in vineyards [4]. The mentioned approach for mapping, like any other SLAM approach, requires the robot to be physically available for navigation in the terrain. This represents an inconvenience for large dimension terrains like steep slope vineyards in Douro Region, for example, Sogrape wine production at "Quinta do Seixo" relies on 71 ha of vineyard [5]. The mapping process with a ground robot would result in a hugely time-consuming task which may be a market barrier for the robot. An alternative relies on detecting the rows of the vineyard from aerial/satellite imagery to construct a map ready for path planning of Autonomous Ground Robots (AGV).

This task requires two stages: segmentation of vineyards from satellite/aerial images; and processing of vineyards regions in order to detect paths between vegetation from which is built the occupation grid map. This article focuses on the first stage. This work considers a machine learning based approach (SVM classifier with Local Binary Pattern (LBP) based descriptor) to perform the vineyard segmentation from public satellite imagery. Besides, this approach is able to identify vineyards or to perform a more advanced classification considering other classes (such as roads or trees). In contrast to deep learning based approaches, which require large data-sets [6], our approach requires less training images and it is more time efficient during the training process.

Section 2 presents related work to path planning and agricultural image processing from aerial or satellite imagery. Section 3 describes the proposed machine learning approach for vineyard detection and section 4 contains the results of the vineyard segmentation. The paper conclusions are presented in section 5.

2 Related Work

Path planning consists in the task of finding the best possible path between two points, being that the definition of best path changes according to the required task. There are several path planning approaches such as potential field planners, RRT (Rapidly-exploring Random Tree), and grid map based search algorithms like Dijkstra or A*. [1] [2] Usually, path planning algorithms require a map with the environment characteristics (obstacles), and image analysis of aerial or satellite images could simplify the mapping process. The detection of vegetation characteristics resorting to aerial imagery is a recurrent topic with several works for diverse agricultural cultures. Works with Images obtained by Unmanned Aerial Vehicles (UAV) are predominant, but there are some approaches with very high-resolution satellite imagery. Mougel *et al.* [7] resorts to this type of images for tree crops monitoring performing tests with a regular vineyard and a peach groove to identify patterns. Karakizi *et al.* [8] also proposes a vineyard detection tool which extracts the vine canopy with very high-resolution satellite data. Torres *et al.* [9] presents a 3D monitoring tool with UAV technology. In the first stage, a digital surface model is created. This is followed by the Object-Based Image Analysis (OBIA) techniques used to extract several features from the vegetation such as canopy area, tree height and crop row position. OBIA is based on Otsu method. This is used to detect, classify, and perform automatic threshold in plantations of maize, wheat and sunflower with images captured from conventional and multispectral cameras placed in a UAV [11]. OBIA is also the chosen method for a cropland mapping tool with aircraft imagery. Different lands are identified with geographical object-based image analysis and random forest classification [10]. The Hough transform method is a technique for detecting patterns of points such as lines or parametric curves. This technique is widely used for crop rows detection either with aerial images or ground images [12] given that most of the plantations are disposed in straight lines. Ortiz *et al.* [13] [14] proposes systems for weed mapping in crops using UAV imagery. In order to improve weed discrimination, the relative position of the weeds is given with respect to crop lines. Therefore, the authors present an accurate method to detect the crop in rows based on the Hough transform. Crop row detection is also a common case study for vineyards, resorting to different types of approaches. Smit *et al.* [15] developed a method to detect vine blocks, rows, and individual vines. The segmentation process is made with a combination of threshold and graph-based technique from multispectral images. Delenne *et al.* [16] provides a methodology for vineyard delineation using aerial images with a row extraction tool. This tool assumes that the rows are parallel and starts by filling the parcel with a high number of orientated lines, eliminating the false rows with a local minima identification. Further, to extract vine canopy vine rows, a study was performed comparing the following four methods: k-means cluster, artificial neural network, random forest and spectral indices, concluding that k-means method had the lowest performance while other methods had a satisfactory performance [17]. A skeletonization method with high resolution unmanned aerial systems (UAS) imagery was considered to reduce the complexity of agricultural scenes, simplifying the classification of features like vine rows. [18]. Comba *et al.* [19] developed a work similar to the approach proposed in our work. With an image processing algorithm constituted by three steps (dynamic segmentation, Hough space clustering and total least squares), the authors are capable of segment vine rows in aerial images. The final result is an image liable to use as a map for path planning algorithms in AGVs. However, this is applied to a normal vineyard, without relevant slopes and total straight vine rows. In fact, all of the crop row detection state of the art address problems of straight line vegetation. Steep slope vineyards have the characteristics containing high slope terrains with curve vine rows. To the best of our knowledge, there are no approaches to segment steep slope vineyards which contain high sloppy terrains and inconstant vegetation curvatures.

3 Proposed model for Vineyard segmentation

The classification task was based on a Support Vector Machine (SVM) classifier running on ROS (Robot Operating System)[3]. A Region Descriptor is extracted

[3] ROS - http://www.ros.org/

and used as input for the SVM classifier. Based on the training step, this tool is able to classify each image pixel according to the desired class objects. Fig. 1 illustrates a diagram with information flow of the classification process. The descriptor is based in LBP (Local Binary Pattern) codes, a grey-level invariant texture primitive. The non-parametric LBP operator was introduced by Ojala *et al.* [20] [21] for textured image description. The Original LBP works in a grid size of 3×3 for a given arbitrary pixel over an input grey-level image. The LBP code is computed by comparing the grey-level value of the centre pixel and its neighbours within the respective grid. The grey-value of the neighbouring pixels not covered by the grids are estimated by interpolation. The threshold stage is carried out with respect to the centre pixel, resulting in a binary number called LBP code. To describe the image texture, a LBP histogram (hLBP) is built from all binary patterns of each image pixel, as shown in Equation (1), where K is the maximal LBP pattern value. Based on hLBP, two types of descriptors are constructed: *hLBP by colour* and *hLBP plus colour*, Fig. 2.

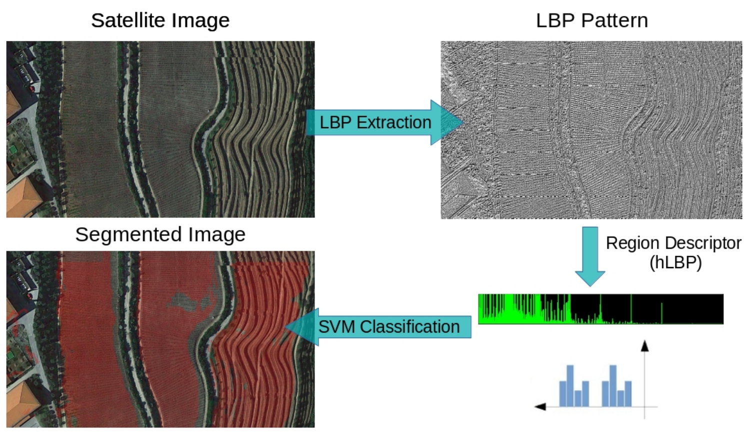

Fig. 1: Information flow of the classification process

$$\begin{cases} H(k) = \sum_{m=1}^{M} \sum_{n=1}^{N} f(LBP_{P,R}(m,n),\ k), \quad k \in [0, K] \\ f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \end{cases} \tag{1}$$

The *hLBP by colour* contains one LBP histogram per colour, discretizing the colour ranges into n colours in RGB (Red, Green and Blue) space. The length of this descriptor is calculated with the multiplication between the number of LBP codes and the number of colour ranges. The LBP uniform variant is selected with 8 colour ranges. Considering $LBP^{u}_{8,2}$, the descriptor size has $59 \times 8 = 472$ bins. With this descriptor, the extractor in each pixel detects the related colour range and increments the histogram bin related to the LBP code extracted for

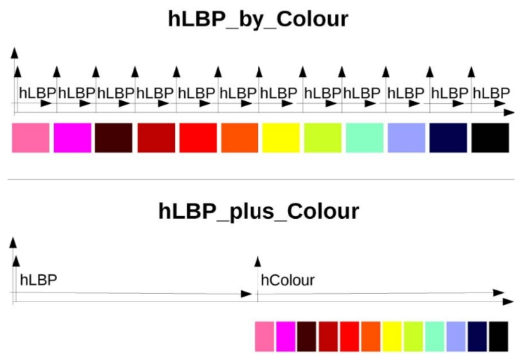

Fig. 2: Two descriptors selected: *hLBP by Colour* and *hLBP plus Colour* [4]

that pixel. *hLBP plus colour* is composed of two histograms, one for LBP codes and other for colour ranges. Its length is given by the number of LBP codes plus the number of colour ranges. Considering the $LBP_{8,2}$ with 8 colour ranges, the descriptor size is $256 + 8 = 264$ bins. With this descriptor, the extractor detects in each pixel the related colour range and increments the histogram bin related to that colour. Then, the pixel LBP code is extracted to increment the histogram bin related to that code [4].

These descriptors (*hLBP plus colour* and *hLBP by colour*) will feed a SVM classifier. SVM is a machine learning approach usually suited for two-group classification problems. The concept implements the following idea: input vector are non-linearly mapped to a high-dimension feature space. In this feature space, a linear decision surface is constructed [22]. Considering a problem of separating the set of training data $(x_1, y_1), ...(x_m, y_m)$ into two classes, where $x_i \in \mathbb{R}$ is a feature vector and $y_i \in \{-1, +1\}$ its class label. Assuming that the two classes can be separated by a hyperplane $w \cdot x + b = 0$ in some space $\mathbb{H}$, the optimal hyperplane is the one that maximizes the margin. A more detailed explanation about the SVM theory and libSVM (one of its variants implementation) is described by Chang *et al.* [23]. Although the SVM is originally designed for binary classification, there are extensions for multi-class scenarios. Typically the problem is decomposed into a series of two class problems, for which one-against-all is the earliest and one of the most widely used implementations [24].

4 Tests and Results

The *hLBP by colour* contains one LBP histogram per colour, discretizing the colour ranges into n colours in RGB (Red, Green and Blue) space. The length of this descriptor is calculated with the multiplication between the number of LBP codes and the number of colour ranges. The LBP uniform variant is selected with 8 colour ranges. Considering $LBP^{u}_{8,2}$, the descriptor size has $59 \times 8 = 472$ bins. With this descriptor, the extractor in each pixel detects the related colour range and increments the histogram bin related to the LBP code extracted for that pixel. *hLBP plus colour* is composed of just two histograms, one for LBP codes and other for colour ranges. Its length is given by the number of LBP codes plus the number of colour ranges. Considering the $LBP_{8,2}$ with 8 colour ranges, the descriptor size is $256 + 8 = 264$ bins. With this descriptor, the extractor detects in each pixel the related colour range and increments the histogram bin related to that colour. Then, the pixel LBP code is extracted to increment the histogram bin related to that code [4].

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(a) Image 1 (b) Image 2

Fig. 3: Satellite Images considered for vineyard detection

4.1 Vineyard detection with two classes

In this stage the SVM was trained to identify two classes from the satellite images: The "Vineyard" class contains different types of steep slope vineyard cultures such as traditional, one-line, two-line, terrace vineyards. The "Others" class contains roads, houses, river or other cultures. For this purpose, a data set was built with several sub-images belonging to the two classes, as specified in 1. In general, the number of images for the class "Vineyard" is larger due to the richness of wine cultures in the Douro Region. A bigger area was covered to obtain the images of the class "Others" in order to avoid a larger difference of images between the two classes. Some samples of these images are represented in Fig. 4. However, not all the images are used in the training process of the SVM. Some images are taken from the data set to test their accuracy after the training. The result of the algorithm accuracy test is shown in table 1, where the tests of the SVM classifier are performed by running the detection with the test images of the data set.

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(a) Block images of class "Vineyard" (b) Block images of class "Others"

Fig. 4: Samples of Image Blocks for SVM train and test

Table 1: Number of images available for the SVM train and test process

Classes	Nº of images	Train Images	Test Images	**SVM Classification Test Accuracy**					
				hLBP_by_colour		Accuracy (%)	**hLBP_plus_colour**		Accuracy (%)
				Vineyard	Others		Vineyard	Others	
Vineyard	1310	1138	172	169	3	98	167	5	97
Others	1141	1028	113	4	109	96	5	108	95

Table 1 presents the training accuracy based on some images from the training dataset. In the classification of sub-images from the class "Vineyard", 5 images were classified as "Other", giving an accuracy of approximately 97 %. However, this is based only in a small set of random sub-images selected to perform the test. To calculate the accuracy after running the detection, each image pixel will be compared to the same pixel in a ground truth image, revealing if that pixel was correctly identified. The results are expressed in table 2, where TP and FP are True Positive and False Positive respectively. This table presents the accuracy and the metric F1 score common for binary classification problems.

This metric combines, with a harmonic mean, Precision and Recall metrics. Recall is the number of items correctly identified as positive ("Vineyard") out of the total true positives ("Vineyard" and false "Others"). Precision is the number of items correctly identified as positive ("Vineyard") out of the total items identified as positive ("Vineyard" and false "Vineyard") [25]. So the maximum Recall minimizes false negative (false "Others") while maximum Precision minimizes false positives (false "Vineyard"). The segmentation results have an average accuracy of 90.05 % with the descriptor *hLBP by Colour* and 86.9 % with the descriptor *hLBP plus Colour*. The F1 score is also greater with the first descriptor, indicating that the number of false classifications is bigger with *hLBP by Colour* .

The images presented in Fig. 3 were considered to run the SVM classifier and the results are expressed in Fig. 5 using the descriptor *hLBP by Colour* and in Fig. 6 using the descriptor *hLBP plus Colour* . The colour map is related to the probability of each pixel to belong to the class "Vineyard" where blue represents the lowest probability and red the highest.

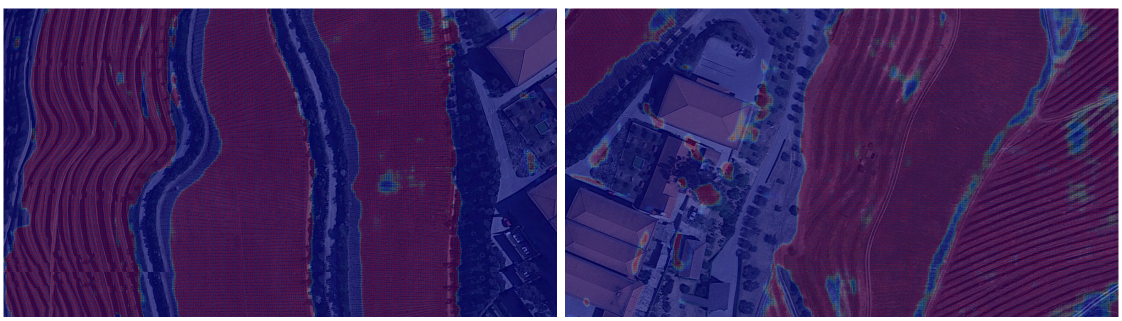

Fig. 5: Detection Results in colour map of class Vineyard using *hLBP by colour*: Blue: Low probability; Yellow: Medium probability; Red: High probability

Table 2: Detection Accuracy with Ground Truth Image for two classes detection

	Classes	**hLBP by colour**		Accuracy	F1	**hLBP plus colour**		Accuracy	F1
		TP	FP	(%)	Score	TP	FP	(%)	Score
Image 1	Vineyard	240857	16291	**92.4**	0.934	222690	25605	**89.6**	0.912
	Others	167320	17389			144096	17192		
Image 2	Vineyard	257025	7336	**87.7**	0.942	264691	11761	**84.2**	0.941
	Others	15667	24124			151251	21579		

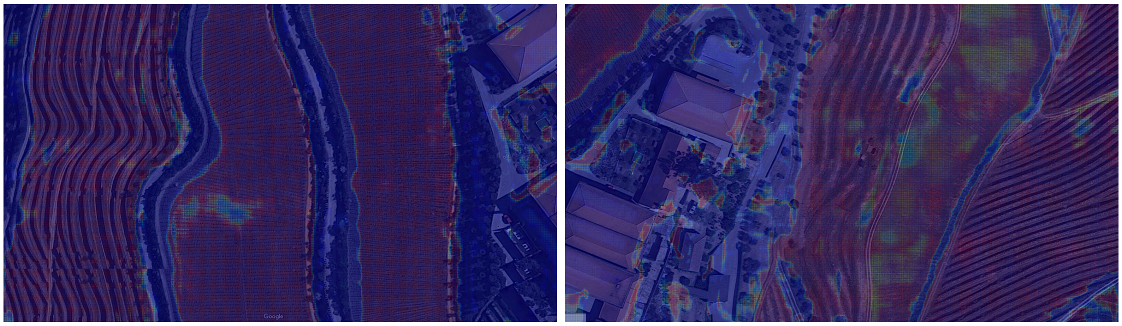

Fig. 6: Detection Results in colour map of class Vineyard using *hLBP plus colour*: Blue: Low probability; Yellow: Medium probability; Red: High probability

4.2 Vineyard detection with four classes

The extraction of more information from the satellite images, such as roads (for car traffic) or trees plantation, could be useful for other agricultural information systems. So, the SVM was trained considering four classes: Vineyard, Roads, Trees and Others. A new data set was created for the train and test process, with several images representing each class (table 3). For this stage, only the descriptor *hLBP by colour* was considered, as the other descriptor has been shown to be less accurate in the preliminary experiments.

Table 3: Number of images available for the SVM train and test process and SVM Test Accuracy

Classes	Nº of images	Train Images	Test Images	**SVM Classification Test**				
				Vineyard	Trees	Road	Others	Accuracy (%)
Vineyard	1251	1091	160	153	4	1	2	96
Trees	433	393	40	2	38	0	0	95
Road	220	200	20	1	0	17	2	85
Others	294	242	52	2	2	0	48	92

The results are exposed in Fig. 7, where each class is represented by its corresponding colour. The accuracy details for each class are described in table 4, where TP and FP represent True positive and False Positive respectively. The average accuracy for the classes "Vineyard" and "Others" is 87.6 % while the detection in classes "Trees" and "Roads" have lower accuracy. One of the reasons for these results could be present in the resolution of the image, which might be too low to detect such details. The reduced number of images in the training data-set for the class "Road" also explains the poor classification results.

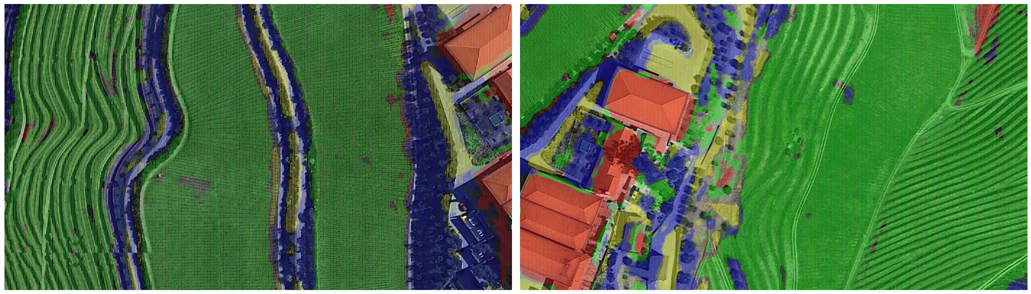

Fig. 7: Detection Results with 4 classes: Green - Vineyard; Blue - Trees; Yellow - Road; Red - Others

Table 4: Detection Accuracy with Ground Truth Image for four classes detection

Classes	**Image 1**		Accuracy	**Image 2**		Accuracy
	TP	FP	(%)	TP	FP	(%)
Vineyard	356779	22936	**94**	341577	56412	**85.8**
Trees	84939	62139	**57.8**	28906	39848	**42**
Road	7966	17277	**31.6**	16137	24173	**40**
Other	24129	7142	**77.2**	61666	4355	**93.4**

5 Conclusions

The proposed approach is capable to perform the segmentation of steep slope vineyard considering image satellite. The vineyard detection has an accuracy higher than 86 % for all the performed tests, while for other classes the accuracy decreases. This happens because the training data set has more vineyard images than other images classes (roads, trees). The two proposed descriptors imply different results, where *hLBP by Colour* is more accurate than *hLBP plus Colour*. However, *hLBP plus Colour* has almost half of the size, decreasing the computational cost, not relevant for this kind of applications. Considering the simple case - single class classification - the detection accuracy reaches 92.4% with *hLBP by Colour*, and 89.6% with *hLBP plus Colour*.

Considering the approach using four classes, the classes "Vineyards" and "Others" accuracy was higher than 86% and 77%. The other two classes (Roads and trees) got a maximum accuracy of 58%. This happened due to the lower number of images available for the training data set.

As future work, this approach will be extended with the second stage - detection of paths between vegetation, that is, the free space between vine trees for robot's navigation. This will be useful for path planning tasks in autonomous ground robots. By detecting the vegetation and the free paths is possible to extract an occupation grid map for path planning algorithms, avoiding time-consuming for Robot setup of SLAM operations. To accomplish this, a more detailed classification will be performed in the segmented images of this article. The same SVM classifier will be tested using lower resolution images for the training step, and possibly a different region descriptor, i.e., HSV (hue, saturation and brightness) colour. Images with higher resolution or even different wave ranges (Normalised Difference Vegetation Index (NDVI)) will be tested.

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