Vegetation Filtering using Colour for Monitoring Applications from Photogrammetric Data

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Abstract: Photogrammetry is one of the widest techniques used to monitor terrain changes which occur due to natural process and geological natural risk zones. In order to carry out terrain monitoring, it is necessary to eliminate all the non-ground elements. One of the most variable elements in this monitoring is the presence of vegetation, which obscures the ground and can significantly mislead any multitemporal analysis to detect terrain changes. Therefore, the focus of this paper is about how best to filter the vegetation to attain an accurate reading of the terrain. There are several methods to filter it based on colourising an excessive greenness vegetation index or non-visible channels as the IR in the well-known index NVDI. However, achieving this kind of information is not always possible because its high cost. Instead this channel we can add new information using the HSV colour space obtained from the RGB information. In this paper, we propose a double possibility, on one hand work with RGB+HSV for a supervised segmentation on images. On the other, to use excessive greenness vegetation indices and RGB+HSV for the segmentation of point clouds. The results shown that the use of additional channels HSV can significantly improve the segmentation in both studies, and therefore render a much more accurate assessment of the underlying terrain.

1 INTRODUCTION

Monitoring active geological hazard zones is a common activity developed by public institutions and scientific groups. The objective is to improve understanding of these events, to better predict their occurrence and therefore minimise any humanitarian impact. Some of these geological movements are preceded by slow movements that can be detected, that are essential to monitor (Jaboyedoff et al., 2012) (Kamps et al., 2017). Therefore, the repetition of the surveys to measure, analyse and map any changes over time is necessary in active zones (Niethammer et al., 2012) (Travelletti et al., 2012) (Barbarella et al., 2015) (Núñez-Andrés et al., 2019). Of the types of hazards classified according to the Varnes classification (Varnes, 1978) we will limit the current study to rockfalls. Therefore, our area of study is quasi-vertical rocky walls, and the unstable blocks are the monitoring objective.

In order to carry out this task, several geomatics techniques are commonly used such as surveying with total station, GNSS (Global Navigation Spatial System), LiDAR, TLS (Terrestrial Laser Scanning) and photogrammetry methods.

During last decade digital photogrammetry has become commonly used for such monitoring applications. This includes both terrestrial and aerial methods, with RPAS (Remotely Piloted Aircraft Systems) becoming increasingly prevalent. However, in using RPAS systems we have to considerer flight restrictions in many countries, mainly in protected natural zones (Dolan & Thompson, 2014)(Stöcker et al., 2017). In these cases, only the terrestrial option is possible.

Stereo-photogrammetric methods are the most widely applied since they allow us to build 3D models of the terrain from the raw photographic data (Eisenbeiβ et al., 2005) (Roncella et al., 2014) (Tziavou et al., 2018). The result of a digital

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photogrammetric survey is a 3D point cloud with similar characteristics to a laser scanning survey but at a cheaper cost.

However, regardless of the method used, the key challenge to obtaining accurate results - either for real time or multitemporal change monitoring via punctual campaigns - is the existence of elements that are not bare ground which therefore have to be eliminated. As a result, before the change analysis can occur a process of segmentation or classification ground/non_ground must be done.

One of the main elements that can mislead any analysis of the ground is vegetation. It suffers gradual variations due to its own growing, seasonal changes of colour and morphology, disappearance, etc. Therefore, it is necessary to detect and eliminate it before the terrain changes and movements detection analysis.

Using LiDAR's sensors mounted on planes or RPAS allows an easier filtering because they capture several signal echoes that allows us to classify data points as either ground or non-ground. However, its high cost and the difficulty to obtain data with an aerial LiDAR on a vertical rocky wall, where the rockfalls happen, invalidate its choice.

The alternative is to work with photogrammetric process and use the color information to segment the point cloud. In this case, nowadays there are several solutions: commercial software's and free plugins that deal with this problem but they only achieve a partial solution, it remains as a difficult issue.

This paper establishes a new approach to perform the segmentation of ground/vegetation on rocky wall faces. The vegetation must be excluded from the monitoring since its changes are not related with terrain movements. In the next sections, we provide two options to exclude the vegetation, which work directly with the original images, before building the model or with the point clouds.

2 METHODOLOGY

There are a lot of methods to detect vegetation from satellite and airborne images. Most of them uses vegetation indices obtained from different channels, with NDVI (Normalized Difference Vegetation Index) (Xue & Su, 2017) being one of the most known. It is calculated from the Red and NIR (Near Infrared) channels. Therefore, it could be applied in terrain images from hyperspectral cameras. The main drawback of this solution is the high cost of this equipment.

For a point clouds segmentation, there are a variety of methods for MMS (Mobile Mapping Systems) urban survey. Most of them are based on information such as signal intensity in addition to geometry (Yadav et al., 2016). In natural environments, these methods are less efficient since natural features such as vegetation do not fit to regular shapes.

If the point clouds come from a photogrammetric process, the algorithm to segment bare ground and vegetation involves the use of the height information without taking into account the error in it (Becker et al., 2017). Moreover, this information is not useful when we are working on a vertical and irregular rocky walls, source areas of rockfalls. Therefore, to look for other options is necessary.

We work with two types of data: original images and point clouds. In the first case, having classified the image into ground and non-ground areas, a binary mask can be applied to the images before the photogrammetric process. In this way, only the ground areas will be used to build the terrain model.

On the other hand, after the point cloud classification process we get two files, one with the vegetation and other with the bare ground. The last one is that can be used for the terrain change analysis.

The approach that this paper proposes is based on using only the RGB channels, and the indices and HSV colour space derived from this information.

The vegetation indices are based on the visible channels used in the VVI (Visible Vegetation Index) and the ExG (Excessive Greenness), equation (1) and (2) respectively (Ponti, 2013).

The VVI values are between 0 and 1, where low values correspond to bare ground, and values near 1 to vegetation. The vector RGB_0 is the reference green colour and *w* the weight (Ponti 2013).

$$VVI = \left[\left(1 - \left|\frac{R - R_0}{R + R_0}\right|\right)\left(1 - \left|\frac{G - G_0}{G + G_0}\right|\right)\left(1 - \left|\frac{B - B_0}{B + B_0}\right|\right)\right]^{w} \quad (1)$$

Before calculating the ExG it is necessary to normalize the values RGB. This is a continuous index, as in the VVI the low values indicate the presence of bare ground and the highest imply vegetation.

$$ExG = 2G - R - B \quad (2)$$

RGB colour models are commonly used since they refer to the biological processing of colours in the human visual system (Loesdau et al., 2014). However, they are not always is the best. According to the literature, the Hue-Saturation-Value (HSV) colour space has more robustness under variable illumination conditions. Therefore, this study further assesses the HSV colour space for automatic vegetation-ground classification. The conversion from RGB to HSV is described in the equations (3)(4)(5)

$$V = \max(RGB) \tag{3}$$

$$S = \begin{cases} 0 & if\ \max(RGB) = 0 \\ 1 - \dfrac{\min(RGB)}{\max(RGB)} & other\ cases \end{cases} \tag{4}$$

H= (5)

- Non defined $if\ max = min$
- $60\frac{G-B}{max-min} + 0° \quad if\ max = R\ and\ G \geq B$
- $60\frac{G-B}{max-min} + 360° \quad if\ max = R\ and\ \ G < \mathrm{B}$
- $60\frac{G-B}{max-min} 120° \quad if\ max = G$
- $60\frac{G-B}{max-min} + 240° \quad if\ max = GB$

The range of values for the H coordinate is from 0º to 360º, from 0 to 1 for S and V, since the RGB values are normalized.

2.1 Data

The study was carried out in several zones of Catalonia, although we show in detail only one of them. This area belongs to the *Riera Gavarresa* (Catalonia, Spain). It is a slope with an approximate area of 600 m^2. A set of stereo-photogrammetric images taken in two different seasons, spring and summer, are available with a GSD of 2 cm.

For the photogrammetric process, block adjustment and georeferenced, we have used the Agisoft Metashape software.

The 3D point cloud model obtained has a high quality, Figure 1. It is dense, homogeneous and has information of the rocky wall and the vegetation around and on it. The vegetation covers the top of the slope with trees, the face of the slope is covered in some parts by shrubs, and where it finishes the ground is covered by grass some bushes and small trees.

One option that could have been used would be the tools implemented in Agisoft Metashape to eliminate vegetation and to achieve a model free of vegetation. That can be compared with the one obtained with our approach. But it was not possible because the software does not allow us to customize these filtering tools and part of the vegetation remains.

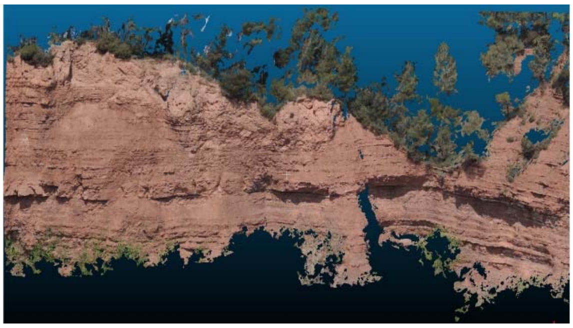

Figure 1: 3D point cloud model obtaining by photogrammetry.

2.2 Image Classification

The image classification was carried out using the commercial software ENVI.

In the case of working with the original images we have chosen a supervised classification with both visible bands, RGB, and six bands, RGB+HSV.

The first step was to build the RGB+HSV images. After that, the regions of interest (ROI's) were chosen to train the classification model. We considered three different set of classes:

- 5 classes: sky, vegetation, shadow in vegetation, rocky wall, shadow in rocky wall.
- 4 classes: sky, shrubs and grass, trees, rocky wall.
- 3 classes: sky, vegetation, rocky wall.

The three classifications were applied on the two images sets: RGB channels, and RGB+HSV.

The image classification was made with two common methods (Richards, 2013), the Euclidean minimum distance and the Maximum Likelihood Estimation (MLE). After the analysis of the results of the classification and the confusion matrix, the first one was discarded and the process was continued using only with MLE. Whilst the general accuracy with MLE is approximately 98% for all the sets, it was roughly 85% using the minimum distance method.

2.2.1 Results

The results obtained for all the images set and all the classification groups are satisfactory for both RGB and RGB+HSV. However, we can highlight a slight improvement when the number of channels is increased.

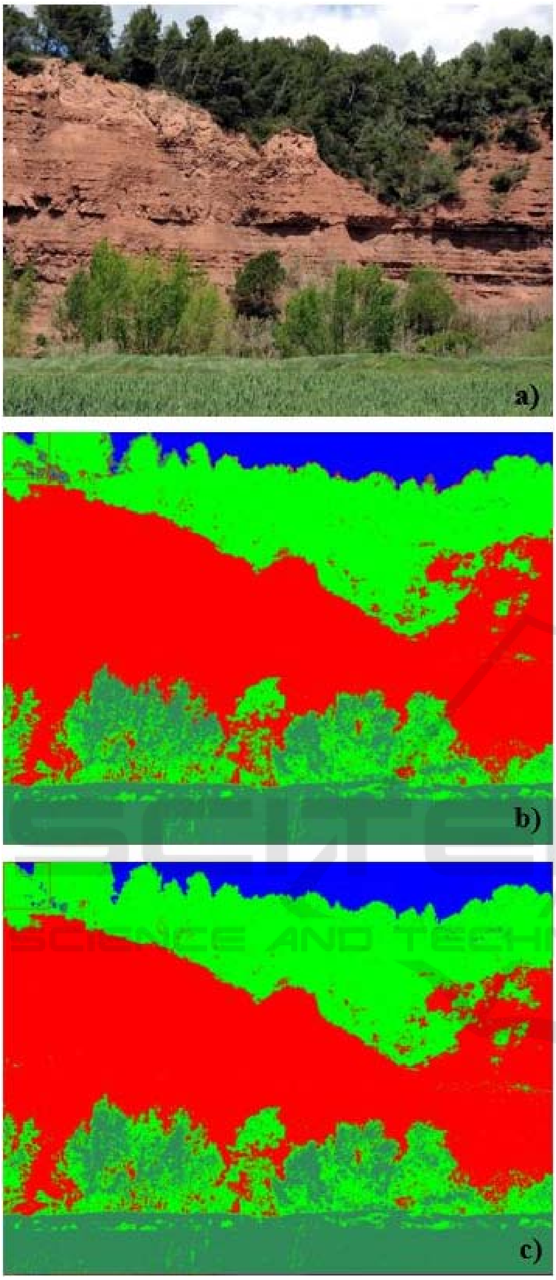

Figure 2: Maximum Likelihood Estimation classification in 4 classes results: a) original RGB image, b) RGB channels, c) RGB+HSV channels.

Figure 2 shows the classification results using four classes. The upper image is the original image, in the centre we locate the classification with an RGB image, Figure 2. b). It can be seen that the boundary between classes is less defined than in Figure 2.c), which uses both RGB+HSV channels, mainly between the sky and trees class.

With regards the general results, in all the cases the use of RGB+HSV images allows to achieve a slight improvement, of less than 1%, in the overall accuracy compared to the RGB-only analysis. However, this improvement is more pronounced in the vegetation classification, overall in the shrubs and grass class, when the number of classes considered is decreased.

Using three, four, or five classes the behaviour is similar. The accuracy in the omission decreased when the additional information of the hue is considered in the classification.

2.3 Point Cloud Segmentation

Working with point clouds, the segmentation has been carried out considering three parameters: the colour indexes VVI, the ExG, and finally with the coordinates of the colour space HSV.

We have implemented in Python language a program to read the point cloud and calculated the two indices and the HSV coordinates.

For the VVI calculation the values for the vector of the reference green colour RGB_0, eq (1), are R_0=60.0, G_0=70.0 and B_0=30.0, and the weight component w= 1.

The problem in this index is to set the reference values, since they depend on the image and the characteristics of the zone.

After the colour space change, it was checked that the hue coordinate, such as the eq. (5) shows its value range from 0º to 360º, is the one that provides most useful information for the segmentation. For this reason, the value and the saturation coordinates have not been considered in the classification.

Analysing the distribution of frequencies for the VVI, ExG and H values it can been observed that they follow a bimodal curve, Figure 3, and the minimum between then could be established as the threshold to segment the point cloud. In this way, during filtering using the ExG index we have considered vegetation points with ExG > -0.02, Figure 3.

In all the areas classified the hue coordinate shows a similar behaviour. The higher values, more than 300º, are located in areas covered by shadows, Figure 4. Therefore, we have to considerer the minimum between the distributions and then the tile to segment correctly the point cloud.

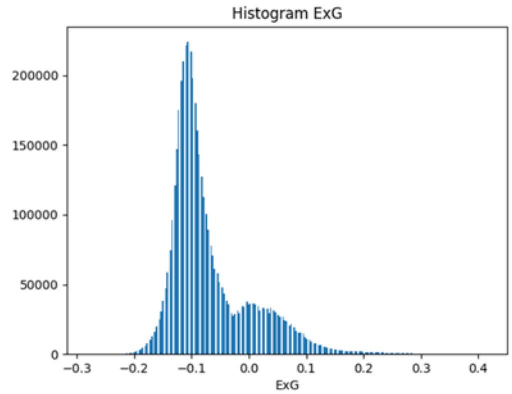

Figure 3: Bimodal curve from the ExG values.

It has been considered that if we have more classes than bare ground and vegetation this approach should be reconsidered to find the thresholds.

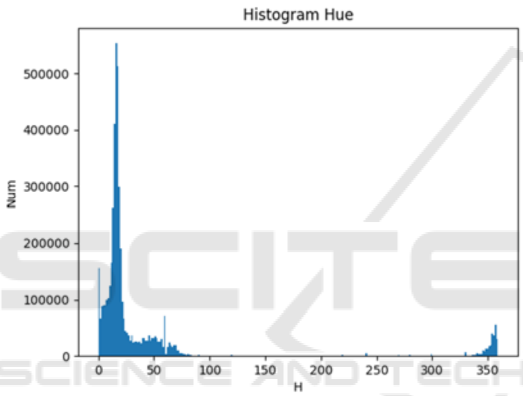

Figure 4: Bimodal curve from the H values.

The result after executing the program are for each index two files, one with the vegetation and other with the bare ground and rocks, i.e. six files are obtaining.

2.3.1 Results

Figure 5 shows the results of the classification using the different indices. In all the images the bare ground has been represented in grey colour. In a qualitative analysis, as the images shown the best results are obtained using the ExG index and the hue value, Figures 5.b) and c) respectively. The worst results are gotten with the VVI, which shows as vegetation the shadow areas.

The Figure 5.d) shows in red the shadow areas where the H value reaches more than 300º. These extreme values are represented in the tile of the histogram as we have mentioned previously.

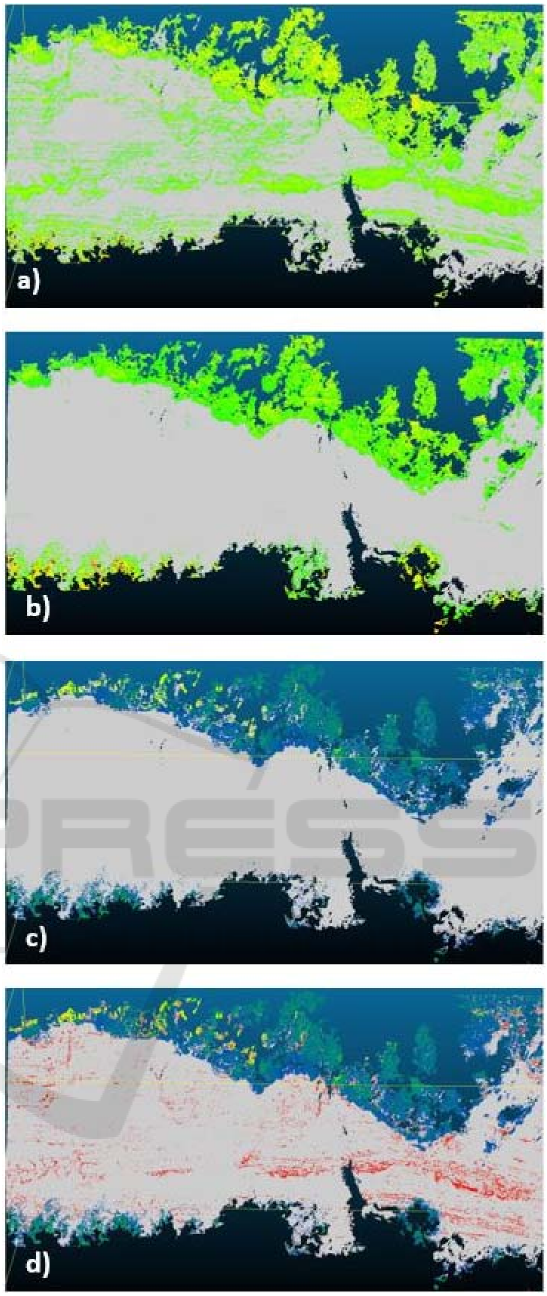

Figure 5: Results after the classification, a) VVI, b) ExG, c) Hue values eliminating the tile of the distribution and d) Hue values with the values higher 300º.

A common problem is due to the lack or existence of misleading information in the treetops. Since the branches and leaves are not in the same position in all the images, by the wind effect, they appear in the 3D model without colour. Therefore, they cannot be classified using this characteristic.

Moreover, we have classified the point cloud with Canupo (Brodu & Lague, n.d.), Figure 6, to test the influence of the use of geometry components in the result improvement. In a qualitative comparison with the results, Figure 5, we can see that there are zones of bare ground classified as vegetation, such as with the use of VVI.

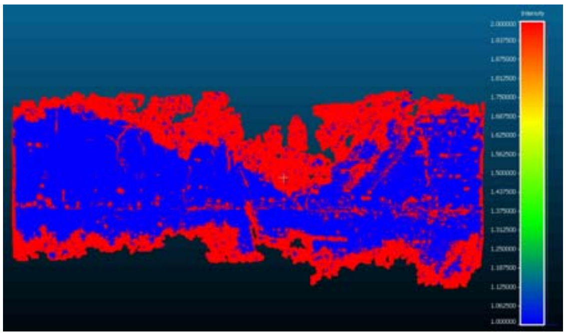

Figure 6: Results of classification with Canupo, in red vegetation and blue bare ground.

Table 1 shows a quantitative comparison of the filter methods: the number of points classify as bare ground, vegetation, and percentages of filtered vegetation points by the three indices. The values of shadows, the tile in the histogram, are not considered for the hue.

Table 1: Number of points in the filtered point clouds and the percentage of the correct vegetation filtered.

	Ground	Vegetation	% filtered
VVI	3.39M	1.09M	75.8
ExG	3.40M	1.08M	94.8
Hue	3.40M	1.08M	95.3
Canupo	3.06M	1.58M	62.5

The ExG and H classify almost the whole of the vegetation points. The percentages of commission are around 2% and 1.5%, respectively, mainly in the zones of shadow boundary between the ground and the bushes. This percentage increases dramatically when we use Canupo.

In other study areas, where the point cloud was obtained by TLS with only an internal camera, the results were worst. Mainly, due to the illumination is not the best, since the sensor takes photographs in an automatic way with the same parameter for all of them.

3 DISCUSION AND FINAL REMARKS

The filters that were used in this study have the advantage that are easy to implement. Moreover, the results let us be optimistic in the vegetation filtering using only colour information though indices or the values of Hue derived directly from the visible bands.

We have used images taken with a common camera, therefore the cost of this sensor is cheaper than other methods. The use of the NIR band could improve the results but these cameras are more expensive if the resolution want to be kept.

The ExG index and the H value in the case of point clouds allows us a good classification in the areas where the model have been built correctly. In elements that appear moved between a photographs and other such as the leaves moved by the wind, the colour is not assigned to the point in the point cloud and therefore cannot be classify by this characteristic.

Whether the classification is made directly on the images the use of the H value added to the RGB bands allow to improve the results without increasing significantly the time of computation.

4 CONCLUSIONS

In the monitoring of rocky massif to prevent rockfalls is not possible to use LiDAR due to the verticality of the walls. Therefore, we cannot take advantage of the use of several signal echoes to classify vegetation. Multi-spectral cameras are an alternative. However, their high cost makes us to discard them.

In this paper, we have proposed the use of the RGB channels for two purposes, on one hand to obtain vegetation indices based on the visible channels and, on the other hand to add additional HSV channels to the images and point cloud previously to classify them.

The results show that the combination of the RGB bands allows us to filter vegetation with methods of simple application using a common camera, therefore it is cheaper than other options.

The image classification using as additional band the Hue value derived of the RGB improves the result. This improvement is higher when the number the classes decrease.

The point cloud classification has good results using the ExG and H values. The success of VVI index is conditioned by the reference vector, whose adjustment depends on the scene to classify and it is more influenced by colour variations and shadows. However, shadows and boundary zones are where more misleading classification exist, in all cases.

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