# Object-based image analysis for detecting indicators of mine presence to support suspected hazardous area re-delineation

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Abstract: In the framework of Mine Action, the extent of Suspected Hazardous Areas (SHAs) is often overestimated. This study investigates the potential of Object-Based Image Analysis (OBIA) for extracting Indicators of Mine Presence (IMP) to support a more precise delineation of SHAs, with the aim of ensuring an optimal use of demining resources. The study area is situated in the Svilaja mountain range in Croatia. Using 3K colour aerial photographs, we implemented two approaches for the extraction of dry stone walls located in an area that displays traces of military activities. The first approach uses object-based class modelling, which describes an iterative process of segmentation and classification. The second approach implements supervised learning techniques based on advanced statistical classification methods, i.e. Support Vector Machines, Random Forests and Recursive Partitioning. The results are compared, the strengths and limitations of both approaches are discussed, and perspectives for further improvements are considered.
Keywords: Feature extraction, Humanitarian Demining, Image processing, Remote Sensing.

## 1. Introduction

The Republic of Croatia is the only heavily mine-affected member of the European Union, a legacy of the conflict associated with the break-up of the former Yugoslavia in the early 1990s. Although Mine Action is highly advanced in this country, about 630 km² are still considered as being Suspected Hazardous Areas (SHAs), i.e. areas where there is suspicion of contamination based on indirect evidence (International Campaign to Ban Landmines, 2013). The extent of SHAs is often overestimated in the databases of Mine Action Centres. In a process known as Non-Technical Survey (NTS), a thorough analytical examination of relevant existing data should lead to their re-delineation. However, up-to-date information on the precise location of important elements for NTS, i.e. Indicators of Mine Presence (IMP) and Indicators of Mine Absence (IMA), are mostly not available. IMP are linked to military activities during the conflict (e.g., bunkers, fortifications), to the presence of strategic locations (e.g., infrastructure such as roads, hilltops), or to the use/disuse of land (e.g., for cultivation) by the local population. This study focuses on the extraction of dry stone walls that are considered as IMP due to their location in a zone with evidence of military activity.

## 2. Study area and data

The study area has an extent of 1 km² and is situated in the Svilaja mountain range in Croatia. In October 2013, a flight campaign was carried out over this area to acquire colour



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aerial photographs (RGB) with a 3K system (Kurz et al., 2012). The aerial photographs were radiometrically calibrated, atmospherically corrected, orthorectified and mosaicked; they have a spatial resolution of 0.15m (Fig. 1a).

## 3. Methods and results

In the study area, dry stone walls are only partly distinguishable from their surroundings as they are built using the material that makes up their environment, i.e. limestone. Therefore, they are not spectrally unique, especially as the 3K data features only three bands in the visible spectrum. Furthermore, they are quite narrow and not always continuous, which makes it difficult to segment them properly. Extracting them is thus a challenge for OBIA; pixel-based methods are more generally implemented for linear feature extraction.

In this paper two approaches were used for the extraction of dry stone walls, and benchmarked in regards to their strengths and limitations.

For the first approach, a tailored ruleset was developed in eCognition (Trimble) software. By making use of an object-based class modelling approach (Tiede et al., 2008; Tiede et al., 2010), which describes a cyclic process of segmentation, image-object border refinement and classification, it was possible to detect and classify the features of interest. As a first step edge detection filters were calculated in eCognition (i.e. Canny and Sobel filter) for the blue band, as dry stone walls are best recognizable in this band. To obtain smoother images with less noise, convolution (i.e. Gaussian Blur) and median filters were applied to the edge detection layers, each with a kernel size of 11 x 11 pixels. In a second step, the contrast split segmentation algorithm was applied, again using the blue band, to divide the image in dark and bright objects based on contrast thresholds within given tiles. During this processing step, relatively bright objects were classified as potential dry stone walls. To reduce the high number of false positives occurring in the surrounding rocky terrain, mainly spatial and geometric characteristics (e.g. density, border index, length/width) as well as the edge density layers and relational features (e.g. difference to neighbouring objects) were used. However, a number of false positives with very similar characteristics to dry stone wall objects still remained misclassified at this stage. Therefore, the preliminary classification was copied to a separate map, i.e. an independent sub-project in eCognition, to perform cyclic growing operations of the currently classified objects. This led to the merging of correctly classified but not connected dry stone wall objects. The resulting elongated dry stone wall objects showed altered geometric characteristics and could then be better differentiated from false positives by using a limited number of further rules. Additionally, a repetitive process of chessboard segmentations of the unclassified areas with increasing object sizes was conducted. During this process, wrongly classified image objects enclosed by unclassified ones could be identified and eliminated in a stepwise manner. At this stage, the classified image objects represented rather coarse areas of interest as significant object resizing had been done. The classified objects from the initial map with the original segmentation were therefore synchronized to the larger areas of interest on the final map. By applying this stepwise procedure most false positives could be removed and almost all dry stone walls were detected (Fig. 1 b). Finally, smoothing of object boundaries was done by applying pixel-based growing and shrinking algorithms.

In the second approach, the multi-resolution segmentation algorithm was used in eCognition for image segmentation. A statistical approach (ESP2) was used to determine the most suitable scale parameter (Drăguţ et al., 2014). The spectral difference segmentation algorithm was used to create a second segmentation level above the first one to produce more relevant objects. In a second step, four classes were differentiated (dry stone walls, rocky terrain, dirt trails and vegetation) by selecting samples on the highest segmentation level. A set of 13 object features, likely to discriminate the objects of interest from the other classes was selected. These features include spectral information (layer means, brightness, skewness, intensity, redness index), geometry (length/width, asymmetry, border index, density) and relations to neighbouring- and sub-objects (mean difference to darker neighbours, mean density of sub-objects). In the next step, feature values of the selected samples were exported to R statistical software for classification with Support Vector Machines (SVM), Random Forests (RF), Recursive Partitioning (RPart) and k-Nearest Neighbour (k-NN) algorithms, using a K-fold cross-validation approach with 25 resamples. SVM produced the best results (mean Kappa: 0.79), followed by RF (0.76) and RPart (0.67). Results obtained with k-NN (0.56) generated many more false positives; they were therefore not used in further processing. To reduce false positives, only objects classified as dry stone walls by SVM and also by either RF or RPart were retained. A few rules were then implemented to resize and merge these objects and to remove the small and dense ones. The ruleset, deliberately kept very simple and short to favour transferability, allowed reducing the number of false positives but not to the point of eliminating them completely. Based on visual comparison, the second approach also detected fewer actual segments of dry stone walls than the first one (Fig. 1 c).

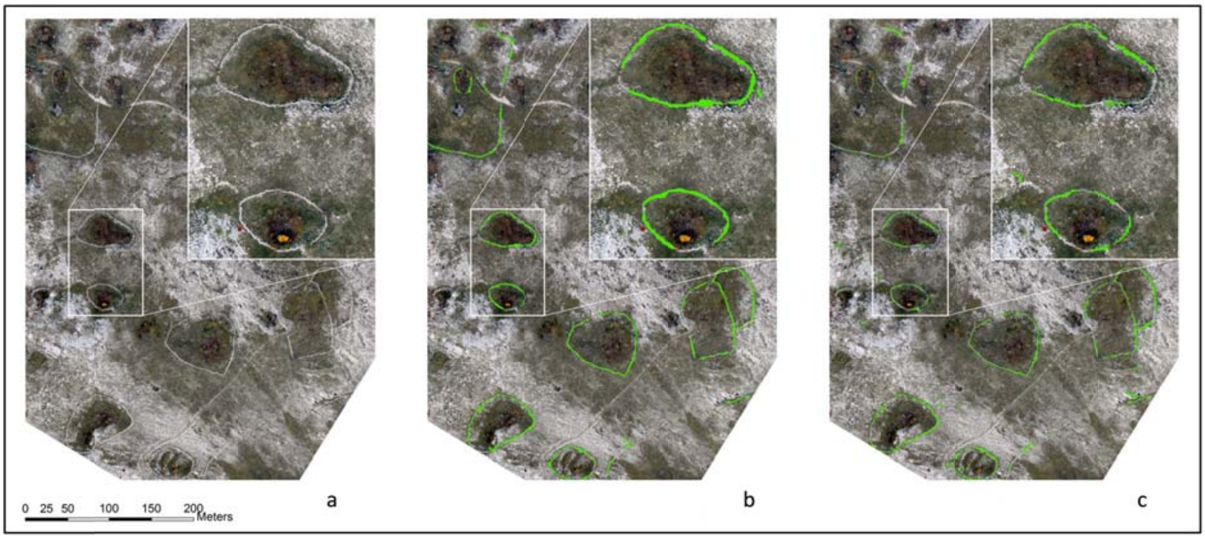


Figure 1. a. 3K data for a subset of the study area, b. with (in green) results of the first method for extracting stone walls (object-based class modelling), c. with (in green) results of the second method (OBIA implementing algorithms for advanced supervised statistical classification).

## 4. Discussion

While dry stone walls are well distinguishable for the human eye on the 3K data, they hardly show any unambiguous characteristics that can be used for a semi-automated computer-based interpretation. In the first approach, a stepwise procedure that makes use of a range of algorithms within eCognition software was developed to detect and classify the features





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of interest. However, the complexity of the ruleset limits its transferability to other areas, although the usage of spectral thresholds was kept to a minimum. In the second approach, the ruleset was deliberately kept very simple and short, so that the limitations concerning the transferability are set by the selection of (i) samples that represent different classes and (ii) the most appropriate set of features to be used by the supervised classifiers. For the latter, statistical analysis could be implemented. Besides, segmentation of dry stone walls might be more efficient if bright line detection was used as additional input (Lacroix and Vanhuysse, 2014). Further research will also address the extraction of other types of IMP. Preliminary exploration showed that factor analysis applied to a set of features allowed their grouping according to three factors characterizing different types of IMP. Features with a high positive value for the first factor (length factor) can be used to classify elongated IMP (e.g. dry stone walls, trenches, fortifications), whereas features displaying high values for the second factor (compactness factor) are valuable for classifying compact objects with a less regular shape (e.g. bunkers). The third factor can be called corrective factor, as it characterizes fuzzy cases such as short trenches or fortifications.

## 5. Conclusions

The semi-automated object-based detection of linear features led to convincing results that can support re-delineation of SHAs. However, for the first approach presented in this paper, further research is needed to improve its transferability, and thus move it to an operational level. As far as the second approach is concerned, further developments should focus on the design of a training set that can be used to classify wider areas, as well as on an approach for selecting the most appropriate object features used as input to advanced statistical supervised classifiers.

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