

A SEMI-AUTOMATIC METHOD FOR DETECTING CHANGES TO ORDNANCE SURVEY[®] TOPOGRAPHIC DATA IN RURAL ENVIRONMENTS

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ABSTRACT:

The detection of changes from aerial imagery is an essential task for Ordnance Survey[®] in order to maintain its topographic database. This paper describes the work of the Research department to create a semi-automatic method for change detection in rural environments. The proposed method uses 4-band aerial imagery and a Digital Surface Model (DSM) generated from the corresponding panchromatic imagery to automatically classify and identify changes between the imagery and the topographic database using eCognition[®] software. These automatically generated 'change candidates' are then manually checked and any necessary map updates are carried out by a photogrammetrist. A trial of the method found 81.7% of the genuine changes which require a map update (completeness), while 25.8% of the 'change candidates' were a genuine change (correctness). These results suggest that the method could provide significant efficiency savings if deployed in production. Other potential uses for the method have also been explored, particularly whether the automatic image classification could be used to filter DSMs to DTMs and whether it could contribute to a new land cover product for the Ordnance Survey[®].

1. INTRODUCTION

1.1 Motivation

Detecting changes to both manmade and natural topographic features is one of the main tasks for any national mapping agency. Ordnance Survey[®], Britain's national mapping agency, updates 222,000km² of 'rural' (1:2500 mapping scale) and 'mountain and moorland' (1:10,000) topographic vector data at least every 5 years. While some of these changes are captured by our network of 300 field surveyors, outside of urban areas the vast majority of map update is completed by photogrammetric capture from aerial imagery. To this end, each flying season Ordnance Survey[®] captures approximately 70,000 km² of aerial imagery using Vexcel UltraCam Xp aerial cameras. At present both detecting changes and updating the topographic data from this imagery is a fully manual process.

Searching aerial imagery for changed topographic features represents a large proportion of the total time that it takes to incorporate these changes into the topographic database. There are currently no off-the-shelf solutions available that can accurately identify changes between a remotely-sensed image and a topographic database. Therefore, the Ordnance Survey[®] Research department has been developing an automatic method of identifying 'change candidates' - features in the imagery that have changed in a manner that requires an update to the topographic database. These change candidates would be used to direct a photogrammetrist to only these potentially changed features as part of a semi-automatic flowline, saving them from manually searching large areas of imagery where there are no changes. Such a system could significantly increase the efficiency of our photogrammetric data capture. However, since the physical appearance of features of interest and the image acquisition conditions can vary greatly, developing a single transferable method of change detection for all the rural imagery we capture across Britain represented a significant challenge.

1.2 Background & Previous Work

Many different methods for automatically detecting topographic change have been presented in scientific literature, several of which have been tested at Ordnance Survey[®]. Many of the techniques rely on a time-series of remotely-sensed data (which may be imagery and/or height data) to generate changes (e.g. Im *et al*, 2008). However, our previous research led us to abandon these approaches as, (1) evolving data capture methods and specifications mean that historic datasets are often difficult to integrate, (2) unless the historic dataset is contemporary to the current state of the topographic database (which for Ordnance Survey[®] is often not the case as field surveyors may have updated the data since the last photogrammetric survey), any changes between the images may not be applicable to the topographic database, (3) it is difficult to filter out the huge number of changes not requiring a topographic update that arise due to differences in illumination conditions, temporary features (e.g. vehicles), vegetation condition etc.

The alternative approach is to directly compare the newly acquired imagery to the topographic database. The simplest way to do this is to classify an image and directly compare this classification to a topographic map to find discrepancies. Several authors report promising results using these methods, though most research focuses primarily on finding changes to buildings (e.g. Matikainen *et al* 2010, Le Bris & Chehata, 2011). Ordnance Survey[®] carried out a project to investigate this approach, the first stage of which involved an extensive evaluation of image classification techniques (Gladstone *et al*, 2007). This research concluded that an object-based image classification using eCognition[®] was the most promising technique for our requirements. eCognition[®] is an object-based image analysis tool that allows the use of object tone, texture, shape, and context criteria with an extensive list of built-in image analysis algorithms, to generate a significantly more

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accurate classification than with pixel-based approaches (Baltsavias, 2004). A rule-based classification method was used as this means it is fully transferable and can be deployed automatically on imagery from different locations and with varying conditions without the need for any training data or calibration. A further benefit of using eCognition[®] is that their Server software makes it suitable for deployment in production environments.

While initial results were promising (Gladstone et al, 2007), a simple image classification approach was an incomplete solution as it did not enable identification of changes to linear features such as fences, walls and paths. Therefore the final approach presented in this paper also uses edge detection methods, which have been successfully employed to detect these types of small linear features (He *et al*, 2009). Edge detection algorithms are built-in to eCognition[®]. This means a single process can be written that uses image classification to find changes to area features and edge detection to find changes to linear features, thus searching for all the changes that require a map update within one automated system.

2. METHOD

2.1 Input Data

The proposed change detection method uses imagery obtained using Ordnance Survey's standard procedures. This means it uses imagery from a Vexcel Ultracam Xp camera, captured at 15-25cm ground sample distance (GSD) for the panchromatic imagery. The corresponding 16 bit 4-band (red, green, blue, near-infrared) imagery is used to create an orthomosaic at the native multispectral capture resolution (a ratio of 3:1 to the pan resolution, so 45-75cm GSD). The imagery is ortho-rectified using the existing OS Land-Form PROFILE[®] Digital Terrain Model (DTM) and mosaicked with 'Most Nadir' seamlines, so there is no manual intervention in its creation.

A Digital Surface Model (DSM) at 50-75cm GSD is generated automatically from the panchromatic imagery, using the image matching process in BAE Systems SOCET SET Next-Generation Automatic Terrain Extraction module (NGATE). ESRI[®] ArcGIS[™] is used to create a slope model and crude normalized Digital Surface Model (nDSM). This nDSM is obtained by subtracting the existing OS Land-Form PROFILE[®] DTM from the DSM. However, this DTM is a 10m grid and has a stated vertical accuracy of only ± 2.5 m per point (Ordnance Survey[®], 2010a), so the resulting nDSM must be treated with considerable caution in the subsequent analyses.

The final input dataset is the topographic data. As well as being used as the comparison dataset for detecting changes, it is used to guide certain elements of the classification (see section 2.2).

2.2 Image classification

The first stage of the change detection process is to classify the image. This classification is used to detect new, demolished or altered area features. The image is classified into seven land cover classes, trees, scrub, grass/crops, unsealed surface, sealed surface, buildings and water. This choice of classes is driven by the specification for our topographic database, which states that changes to all these types of features must be captured. There are additional linear features such as fences, walls and paths that are in our data capture specification but cannot be identified

from this classification, so these features are identified only as part of the change detection processes discussed in section 2.3.

The image classification is a fully automatic process that requires no training data or calibration. This is achieved using a rule-based classification built using the eCognition[®] process tree. The ruleset has been developed using imagery from different geography, illumination conditions and times of acquisition to ensure transferability. The classification is specific to the input data requirements described in section 2.1, the only other known limitation being that the imagery must be captured when vegetation is leaf-on (early May - late September in the UK).

Several steps are taken to maximise the transferability of the classification. Firstly, as much reliance as possible is placed on the DSM, as height data is largely unaffected by variations in image acquisition conditions. Secondly, where rules relating to image tone are used, they are based on normalized ratios of the bands rather than threshold values where possible. However, in certain cases threshold values are necessary. For example, shadow is required as an interim class for filtering during change detection phases. This is classified using a threshold for image brightness that is derived from the input image itself by finding dark objects neighbouring either trees or buildings and calculating a quantile of the brightness of these features. Similarly, threshold values for both image brightness and mean near-infrared are required to classify water. These are calculated using the *a priori* information available from our existing topographic data. Previous observations indicate that features classified as water in our topographic database rarely change land cover type, and when they do it tends to be due to encroachment by vegetation. We therefore calculate quantile values from the objects that fall within water features in our topographic database, after excluding those that are vegetation using NDVI. However, as the input imagery is an orthomosaic there are often significant differences in image brightness across the entire mosaic due to changes in illumination conditions during data capture. Therefore, the seamline polygon file is retained when the orthomosaic is created and is used to constrain the calculation of these threshold values.

2.3 Change Detection

The change detection method finds changes that require a map update in accordance with the Ordnance Survey[®] data capture specification. The definition of what constitutes a change is complex, but generally we are concerned with new, removed or altered buildings, structures, trees, scrub, water, sealed surfaces, roads, paths, fences and walls. These requirements have been distilled into a set of features that we expect to identify from our classification and change detection procedures:

1. New or extended buildings $> 50\text{m}^2$
2. Demolished buildings $> 20\text{m}^2$
3. New areas of trees or scrub $> 1000\text{m}^2$
4. Demolished areas of trees or scrub $> 1000\text{m}^2$
5. New areas of water $> 100\text{m}^2$
6. Demolished areas of water $> 50\text{m}^2$
7. New areas of sealed surface $> 50\text{m}^2$
8. Demolished areas of sealed surface (where it has changed to grass/crops) $> 50\text{m}^2$
9. New linear features (e.g. fences, walls, hedges, roads, tracks and paths) $> 25\text{m}$ long
10. Demolished linear features (e.g. fences, walls, hedges, roads, tracks and paths) $> 8\text{m}$ long

Whilst in certain cases these size thresholds are the same as in the data capture specification (e.g. new areas of trees or scrub $>1000\text{m}^2$), for other features a larger size than the specified minimum is used (e.g. new or extended buildings $>50\text{m}^2$, where the specified minimum is 8m^2). This proved necessary to minimise the number of false positive change candidates. For example, smaller features identified as new buildings were usually errors (caused by issues such as overthrow from tall buildings or DSM ‘drape’ where the DSM fails to accurately model the vertical sides of features such as buildings) or genuine features that we do not want to capture in the topographic database, such as vehicles or overhanging roofs. Initial investigations with our data collection department indicate that these minimum sizes still deliver an acceptably high proportion of the genuine changes, but the thresholds may be reviewed in future if necessary.

The different types of change are detected at different stages of the process and with different techniques. This increases accuracy by ensuring the filtering processes are specific to the causes of false positives particular to that type of change. The change detection processes take place within the same automatic eCognition[®] workflow as the classification stages.

Possible new area features (items 1, 3, 5, 7 in the list above) are found by intersecting the classification result with the topographic data to find discrepancies between them. A series of additional rules are then applied depending on the type of change to filter out the false positives. For new buildings, the most common cause of false positives is DSM ‘drape’ and errors in areas that the image matching software cannot correlate correctly due to deep shadow or repeating textural patterns (e.g. in recently ploughed fields). To remove these false positives rules relating to the slope, shape and brightness of the predicted objects are used. Another common cause of false alarms is temporary ‘clutter’ (e.g. vehicles, spoil heaps), which are filtered by height, slope and shape criteria. For trees and scrub, false alarms are primarily caused by overhanging tree canopies. These are filtered using shape criteria. Finally, for new water features the most common cause of false positives is deep shadow, which is filtered by shape and context.

Possible demolished features (items 2, 4, 6, 8 in the list above) are detected by first intersecting the features in the original topographic database with the classification. However, features that are initially predicted as demolished from the classification undergo additional tests to remove false positives. For example, buildings in the topographic database are flagged as potentially demolished if less than 80% of their area is classified as building. Further checks on the height and perimeter slope of the building footprint from the topographic database are used to minimise false positives caused by low buildings being omitted from the initial classification. Similarly for water features, those predicted as demolished by the classification are tested further using more generous image tone thresholds relative to those used in the initial classification.

Possible new and demolished linear features (items 9 & 10 in the list above) cannot be identified using the classification. Instead Canny edge detection and line extraction algorithms are used to identify significant linear edges in the imagery. For new linear features, all the detected lines that fall outside buildings or lines already in the topographic database are identified as possible new linear features. However, extensive filtering using image brightness and shape criteria is required to reduce the many false positives created during this process by features such

as shadows, transitions between grass and crops not associated with boundary features, tractor lines etc. Tractor lines through crops (created during crop-spraying) present a particular challenge as they often appear visually similar to genuine paths. These are filtered by determining their position relative to the main direction of all detected lines within a given field and to the field perimeter. This enables the process to retain a new path running across a field while filtering out the tractor lines.

Finally, demolished line features are detected by testing the existing ‘obstructing’ lines (which includes fences, walls and hedges) and road, track and path edges from the topographic database against the results of the Canny edge detection and line extraction algorithms. This is done in two stages, to identify any existing line in the database that either appears completely removed or that has a gap of at least 25m within it. The classification is used to mask out areas of trees because the presence of a line feature cannot be verified photogrammetrically where there are overhanging trees.

3. TRIAL RESULTS

3.1 Trial data

The classification and change detection results were tested on a 5x5km area of rural geography near Coventry, West Midlands, UK. The imagery was captured by COWI (a third-party contractor for Ordnance Survey[®]) on 22nd May 2010 at a panchromatic resolution of 25cm GSD. This is the lowest resolution imagery that the method is designed to use, so better results would be expected on higher resolution imagery. The existing topographic data was then updated in ESRI[®] ArcGIS[®] 10 using the ‘change candidates’ produced by the method described above (sections 2.1 and 2.2). The results of this trial are discussed in two parts, first the classification (section 3.2) and then the change detection (section 3.3).

3.2 Classification Results

It is important to ascertain the accuracy of the classification itself as it is instructive in interpreting its suitability as the basis for change detection. It is also relevant as there are other potential applications for the classification output discussed in section 4.2). The classification accuracy is assessed against a stratified random sample of 600 points based on the strategy recommended by Congalton (1991). For the less common land cover types 50 samples were used (water and scrub), while for the more common land cover classes and those with greater intra-class variability 100 samples were used (buildings, sealed surface, unsealed surface, trees, grass/crops). Due to logistical constraints, it was not possible to complete a ground survey. Therefore, the land cover was assessed by manual interpretation of the corresponding pansharpened RGB imagery, which was deemed sufficient given the broad classes involved.

The image and classification result for a part of the test area are shown in Figure 1, below.



Figure 1: Aerial image and classification results (pink = buildings, dark green = trees, mid-green = scrub, light green = grass/crops, yellow = unsealed surface, grey = sealed surface)

The classification error matrix is shown in Table 1.

Class	Reference data							Total
	B	SS	US	W	T	SC	G	
B	86	3	9	0	2	0	0	100
SS	3	89	5	3	0	0	0	100
US	0	9	83	0	0	1	7	100
W	0	3	0	47	0	0	0	50
T	0	0	0	0	91	6	3	100
SC	0	0	0	0	3	36	11	50
G	0	0	0	0	0	1	99	100
Total	89	104	97	50	96	44	120	600
% O	3.4	14.4	14.4	6	5.2	18.2	17.5	-
% C	14	10	17	6	9	28	1	-
Overall accuracy (%)								88.5
Kappa coefficient								0.86

Table 1: Error matrix for classification (B= Buildings, SS = Sealed Surface, US = Unsealed Surface, W = Water, T = Trees, SC = Scrub, G = Grass/crops, % of C = Percent of Commission Errors, % of O = Percent Omission Errors,)

The error matrix for the classification shows that the classification has a high overall accuracy of 88.5% (Table 1). This indicates it is potentially suitable as the basis for an automatic change detection method.

The scrub class has the lowest classification accuracy, with a commission error of 28%. The majority of this error was due to 'rough' grass being misclassified as scrub (also accounting for the majority of the grass omission error of 17.5%). Scrub often displays similar spectral and height characteristics to 'rough' grass meaning that making a satisfactory distinction between these classes is difficult, particularly because the segmentation often fails to split these classes correctly. Errors also occur in residential gardens where grass is often misclassified as scrub because the relatively low resolution DSM does not model 'clutter' in back gardens satisfactorily.

Scrub was also occasionally misclassified as trees (and *vice versa*), which accounts for the vast majority of the scrub omission error of 18.2%. The classification does not use an nDSM height threshold to distinguish scrub from trees, because the nDSM is unreliable (as discussed in section 2.1). Instead it relies on DSM height relative to neighbouring objects, which is also not always reliable. It is not possible to improve the classification using spectral characteristics as the scrub and tree classes can be composed of the same species. Indeed, it is often difficult for a photogrammetrist to manually distinguish between these two classes.

Unsealed surface also had a relatively low classification accuracy, with an omission error of 14.4%. The majority of this error was due to sparse or patchy (low NDVI) grass being misclassified as unsealed surface. Fields that have been cut for hay production, thus exposing grass stubble and bare earth, were also occasionally misclassified as unsealed surface.

Whilst the building classification accuracy looks reasonable, the commission error (14%) was higher than expected for a number of reasons. Unsealed surface (and to a lesser extent, sealed surface) is sometimes misclassified as building due to 'drape' in the DSM. Highly textured ground surfaces (such as recently ploughed fields) occasionally produce errors in the production of the DSM resulting in reasonably large areas of unsealed surface being misclassified as building. Finally, as the imagery was captured during the early part of the flying season some of the trees are covered in blossom. These trees and shrubs exhibit similar height and slope values to buildings, whilst also displaying spectral ratio values which prevent them from being correctly classified as trees. This can result in small areas of vegetation being misclassified as buildings.

The water classification accuracy was better than expected based on previous observations. A lower than expected omission error of 6% reflected the fact that the waterbodies in the test area were relatively spectrally invariant. Higher spectral variation between waterbodies within a scene can cause errors as the threshold values in the classification are set from the scene (as described in section 2.2). In addition, we have previously observed accuracy issues with turbid and part-vegetated waterbodies. The observed commission errors were confusion between sealed surface and water, due to the spectral similarity between water and asphalt or tarmac.

3.3 Change Detection Results

To ascertain the accuracy of the change detection output a rigorous manual comparison was made between the topographic data and the pansharpened RGB aerial imagery, in order to find all the changes that required an update according to Ordnance Survey's capture specification. This was then compared to the automatically produced 'change candidates' to produce the following statistics,

$$\text{Completeness} = (TP / (TP + FN)) * 100 \quad (1)$$

$$\text{Correctness} = (TP / (TP + FP)) * 100 \quad (2)$$

Where:

TP = True Positives, the number of correctly predicted changes requiring a map update

FP = False Positives, the number of predicted changes that are either incorrect or do not require a map update

FN = False Negatives, the number of changes requiring a map update that were missed

Results show a completeness value of 81.7% (compared to a completeness of approximately 90% from fully manual change detection) (see table 2). Considering the large variety of changes included in the method and the very small extent a change can be to require a map update, this result is very good. Completeness values are generally highest for demolished rather than new features, with completeness of 100% for demolished buildings and trees. This reflects the fact that it is easier to test a feature of known class for conformance to that class rather than to find a new feature.

Lowest completeness values were seen for new buildings and new linear features. This is due to the stringency of the data capture specification for these features. The new buildings that are missed are primarily small (5 are <50m², and are therefore not tested for in the method), or single-storey, flat-roofed buildings which are harder to detect. Similarly, 16 of the 26 new lines missed were <25m, so although they are within our specification, they are below the minimum length the method is designed to detect. Most of the remaining false negatives for new lines were alterations to property boundaries, which were particularly difficult to detect as they often coincide with garden 'clutter' such as shrubs and sheds.

The results show a correctness value of 25.8%. In order to completely eliminate the need to manually sweep the imagery for changed features, it is necessary to detect a very high percentage of the true positives present in the scene (i.e. the completeness should be a high value). This was achieved at the expense of a low correctness value (i.e. the method identifies a relatively high proportion of regions which are not true topographic changes). This trade-off is necessary because it is

not possible to achieve a high enough completeness percentage without creating a significant amount of false positive change candidates. However, a relatively high number of false positives is in itself not prohibitive to the success of the proposed method, providing that it is quick and easy for a photogrammetrist to dismiss these false alarms, which we believe to be the case (see figure 2). This is especially true because the proposed change detection flowline has been largely automatic up to this point. To put the reduction of manual checking effort into perspective, the 5km x 5km test site discussed here contains 11184 topographic area features and 30184 topographic line features. Therefore, identifying 799 features as change candidates, represents a small fraction of the topographic data within the area.

The results indicate that correctness was widely variable for the different types of change. New or modified line features had the lowest correctness of 18.9% and 134/301 false positive new line features were due to tractor lines in crop covered fields. A significant amount of work has already gone in to filtering out edges and lines that are detected but are not suitable for topographic update. As discussed in section 2.3 the contextual relationship to other tractor lines in a given field is vital to help eliminate new line feature false positive change candidates. However, any large field that is in practise used by a farmer as two or more separate fields, but is represented as one field in our data, creates problems that cannot realistically be solved using another method without significantly increasing false negatives. The second most common cause of new line false positives (67 out of 301) were field margins or other distinct linear boundaries between two or more spectrally dissimilar crop/grass types. Ordnance Survey® only maps these boundary features where they have fences, hedges or walls associated with them. False positives result where these features are detected but exist without an associated obstructing boundary feature. A further 41 new false positives were due to unsealed paths or tracks, predominantly around the perimeter of fields. Those features, which are temporary (and almost always only accessible by the land owner), are not captured for map update.

New or modified buildings had a correctness of 19.7%. As mentioned in section 3.2, leafless or blossoming trees display similar spectral and height characteristics as buildings at the resolution of the input data used here. The resulting misclassification of trees as buildings accounts for 50 of the 122 building false positive change candidates. A further 34 false positives result from the misclassification of sealed or unsealed ground surface due DSM 'drape' in the input DSM (and therefore also in the nDSM and slope model).

New and demolished buildings and line features account for 67.5% of the total true positive change candidates. This highlights the importance of correctly identifying these types of features, despite them also having relatively low correctness values.

	NB	DB	NS	DS	NW	DW	NT	DT	NL	DL
TP	30	21	28	22	1	5	4	7	70	18
FP	122	39	21	20	1	16	2	11	301	60
FN	8	0	6	1	0	1	0	0	26	4
Cm%	78.9	100	82.4	95.7	100	83.3	100	100	72.9	81.8
Cr%	19.7	35.0	57.1	52.4	50.0	23.8	66.7	38.9	18.9	23.1
Overall completeness = 81.7 %										
Overall correctness = 25.8%										

Table 2: Change Detection results (NB = New Buildings, DB = Demolished Buildings, NS = New Sealed surface, DS = Demolished Sealed surface, NW = New Water, DW= Demolished Water, NT = New Trees or scrub, DT = Demolished trees or scrub, NL = New Linear features, DL = Demolished Linear features, Cm% = % Completeness, Cr% = % Correctness)

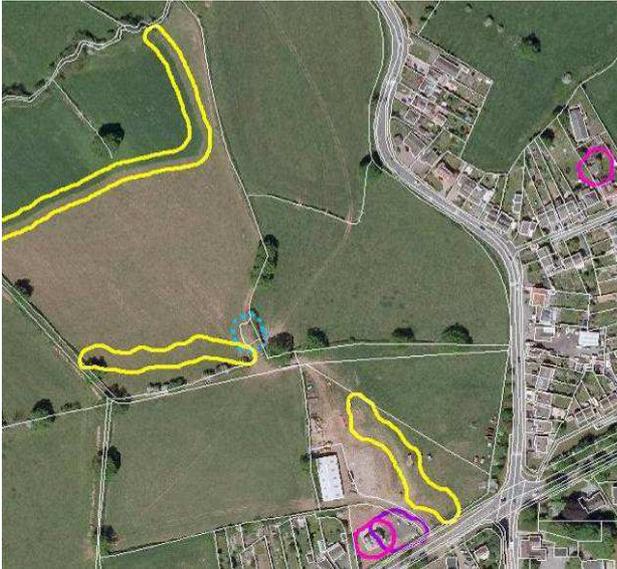


Figure 2: Predicted changes against topographic database (yellow = new line features, pink = new buildings, purple = new sealed surface, blue dashed = demolished water)

It was not possible to calculate potential efficiency savings as part of this trial because we were not able to employ the current topographic data capture production software and the trial was not completed by data capture production staff. However, a previous internal trial indicated that a method similar to that described here could save approximately 50% of the time taken to manually search for features requiring an update.

4. CONCLUSIONS & FURTHER WORK

4.1 Production Trial of a Semi-Automatic Change Detection Flowline

Following extensive testing in the Research department, we are now planning a full production trial of the proposed change detection method. This trial is expected to take place in Spring/Summer 2012. We are currently working with our data collection department to determine the optimum way to display 'change candidates' to photogrammetrists, as this will have a crucial role in determining the usability and efficiency of the overall process. This production trial will allow us to carry out a full assessment of the time saved by using the change detection tool, as well as a more complete accuracy assessment of the results. It is hoped that following this trial the method will be implemented in production.

4.2 Alternative Applications for an Automatic Image Classification

The creation of a fully automatic and highly accurate image classification as part of this change detection project has implications for several other research themes. The image classification could potentially be used both to improve internal processes and as a component of future products.

An initial investigation into using the results of the image classification element of this work to assist in the automatic filtering of DSMs to DTMs has already been completed. This is an important area of research for Ordnance Survey[®] as we are currently assessing how best to produce an enhanced DTM product to replace the existing Land-Form PROFILE[®]. This

project used the first pass filtered DTM created by BAE Systems SOCET SET NGATE that is automatically generated as part of the DSM creation process. The above ground features from the classification (namely buildings, trees and scrub) are then used to automatically run additional local filters in areas where the DSM has not been correctly filtered to ground level. The initial results of this work were encouraging and we intend to pursue this further in future. Increasing automation of the filtering processes could significantly increase efficiency, though some manual intervention will remain necessary for checking the data and adding breaklines for features such as retaining walls.

Ordnance Survey[®] is continually reviewing its product portfolio. One area that several customers have expressed interest in is an improved land cover dataset. As part of a project to investigate this market, several organisations have been supplied with sample data based on the image classification method described above.

4.3 References

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