# AERIAL IMAGE SEGMENTATION FOR FLOOD RISK ANALYSIS

*Neil Robertson and Tak Chan*

Heriot-Watt University
Edinburgh, UK

## ABSTRACT

This paper presents a technique for image segmentation. We demonstrate its efficacy for classsifying high-resolution aerial images. The application is peak water flow estimation in a river catchment in the city of Zurich and the data covers a large rural and urban setting. The output of the segmentation process is used as input to a hydrological model. We introduce a combined, probabilistic, segmentation approach based on colour (the LAB colour space is used), texture (using entropy) and image features (gradients). Classification rates for natural land surfaces and man-made structures are up to 90% and 85% respectively. When the automatic segmentation result is compared to the official land use data and reclassified for use in GIS we achieve an overall classification accuracy of 70%. This new classification is tested on the WetSpa hydrological model and the resulting flow estimate compares favourably with that computed from hand-classified land use data.

***Index Terms*—** Segmentation, Colour, Texture, Hydrological mapping

## 1. INTRODUCTION

The geography of the vicinity of Zurich is, like many places, prone to flooding during storms. In order to make predictions about the impact of certain quantities of rainfall the "runoff" must be considered within a hydrographical model. This is related to the permeability of surfaces which in turn relates to the land use classification. A refined version of the hydrological model has recently been developed, based on the WetSpa distributed rainfall runoff approach. The input to such a model is currently taken directly from a GIS system where the land use is the single most important parameter. In image processing terms this relates to the class of the set of pixels within a certain boundary (i.e. it is a segmentation-by-hand procedure). To acquire detailed land use data is labour intensive and expensive. This is possible in affluent areas (such as Switzerland) but it would be impractical in poorer regions where the human cost of being unable to make predictions about flood-risk would arguably be much greater. The segmentation techniques in the image analysis literature are not able to offer the fine classification of a hand-labelled GIS land use layer (which contains upwards of 34 classes) over a very large dataset. The question motivating this work however is: will the hydrological model be tolerably accurate under the constraints of a coarse, but automatic, segmentation scheme (with, in our case, 5 classes)? If so there exists the possibility of performing flood risk analysis automatically. This paper presents a hybrid segmentation method which is tailored towards aerial image segmentation but is devoid of unnecessary heuristics. The output of the segmentation is used to compute the 60-minute predicted flow at the outlet in the centre of Zurich and is compared with the same model output for the official land use classification.

### 1.1. Prior Work

Image segmentation is an important topic in computer vision and consequently a variety of methods have been applied to the problem ranging from the application of filter banks to agent-based machine learning techniques. Robertson developed an off-line reflective architecture which learns from a corpus of hand-labelled data [5]. Wavelets have been used to speed up the process of classification [3]. Although not applied specifically to aerial images Varma and Zisserman developed an improved method for texture analysis based on the statistics of images, rather than the more popular use of banks of filters [9]. Texture is clearly a significant image feature enabling segmentation, as well as colour. Colour-based segmentation is quite popular. It has been shown that RGB gives reasonable performance in a non-parametric scheme but that colour spaces which separate the luminance and chrominance components perform better over a range of imaging conditions [2]. The features colour and texture have been combined but not addressing the complexities of urban data [1].

Although not the main focus of this paper, for completeness we discuss some of the prior work on hydrological modelling. Various studies have been carried out in the Zurich area to assess existing risks from flooding and other natural hazards. Regarding hydrology, an important study has been the Runoff Process Map of the Canton of Zurich (Abflussprozesskarte des Kantons Zurich), [7]. The Runoff

Thanks to Roland Burckhard and Andres de Moran, School of Built Environment, Heriot-Watt University for access to GIS and hydrological modelling expertise.

Process Map divides unbuilt or unaltered surfaces of the canton into hydrological response units according to the overland and subsurface runoff processes that dominate in each one [7].

### 1.2. Data

The complete set of orthophotos is split into tiles containing 4000 x 4000 pixels each. In total there are around 200 tiles in the dataset. Representative examples of each class are extracted from a hand-labelled section of the dataset which is not then used for further classification or testing. There are 5 classes in our scheme, reduced from the 34 official land use classes. Our class types are generalisations, for example, the official class `building.commerce` and `building.annexe` become examples of the class `building` in the set of classes which can be obtained automatically. The classes we use in this paper are `building`, `paved`, `forest`, `tilled` and `topsoil`.

## 2. AERIAL IMAGE SEGMENTATION

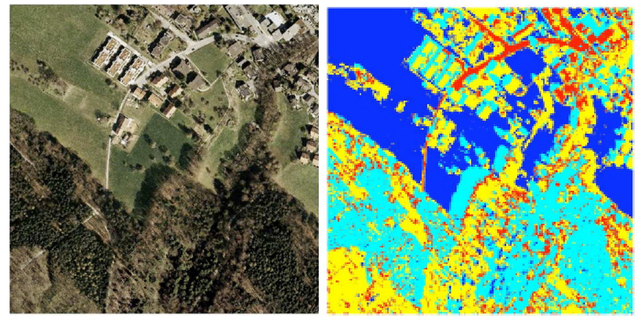
In this section we introduce a three-stage process for segmenting an aerial orthophoto into the five classes defined above. We start with colour then introduce entropy and gradient as image features to refine the segmentation. Final classification is performed by probabilistically combining the results of each stage.

### 2.1. Colour-based segmentation

The first stage of the classification process uses the colour distributions in a non-parametric scheme. We convert to the LAB colour space which is a simple linear transform of the raw RGB pixel intensities [4]. A first approximation to segmentation then follows: for each example pixel in the new image compute the Euclidean distance to the best example each class in the training set. We use the A and B vectors to separate out luminance effects. This normalised distance can be interpreted as the likelihood of that pixel belonging to one of the 5 classes (under the assumption that it is drawn from one of the classes, not an unknown class). An 8x8 median filter is applied for smoothing. The result of this step is shown in Figure 2.1. We note in particular that buildings and roads are likely to be misclassified in this step although 72% of the pixels on average are correctly classified. The exact proportion varying depending on the predominance of each class in the input image.

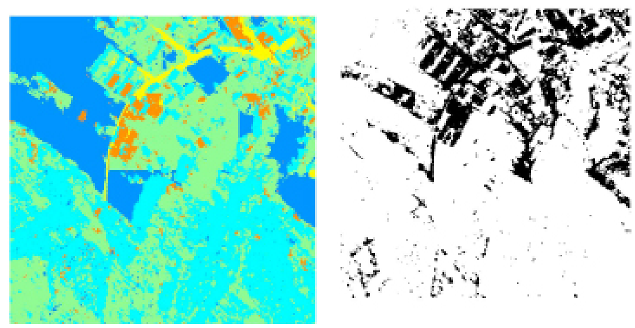
### 2.2. Texture classification via entropy

Given that there will be certain misclassifications due to changes in appearance when colour alone is used we refine the segmentation using texture. Entropy is a measure of the disorderness of a distribution which is related to predictability. Highly textured regions in an image have a higher



(a) (b)

**Fig. 1**. Illustrative example of (a) an input orthophoto TIFF tile and (b) the output of colour-space segmentation



(a) (b)

**Fig. 2**. (a) Output of segmentation via entropy. (b) Gradients used to find man-made features.

entropy than uniform homogeneous regions. Entropy cannot be used on its own since distinct regions may vary in appearance and not entropy. It is defined as $H = \sum_i p_i \log p_i$, where $p_i$ is the likelihood of the ith entry in a pdf (in this case approximated by a normalised histogram of a region of an image). Image blob estimation is computed from the smoothed colour-segmented image using a one-pass connected components algorithm [6]. Each region of the training data is characterised by a mean entropy. Once more, comparing non-parametrically the distance between the entropy of the blobs in the new image to each class results in a probability of that region belonging to that class. The Maximum Likelihood class from this stage alone is shown in Figure 2.2(a).

### 2.3. Image gradients

The colour and entropy features result in 93% of pixels which comprise imaged vegetation being correctly identified over the test dataset, accounting for 3 of the 5 classes. However only 64% of true paved and building pixels are correctly classified this way. This means that in a mainly urban region the overall classification can be as low as 66%. As a final step to improve the result for classes `paved` and `building` we use a gradient filter in combination with a predefined shape

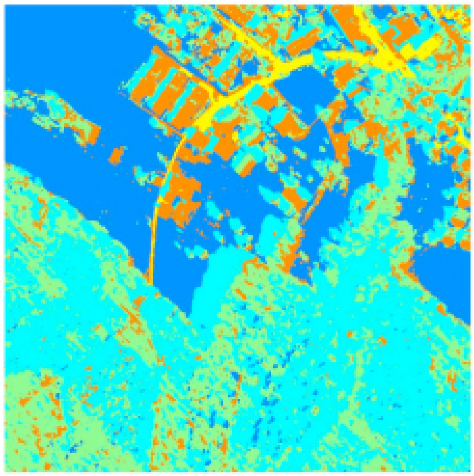


**Fig. 3**. Combined results using colour, entropy and gradients. Note the improved disambiguation between paved areas and buildings.

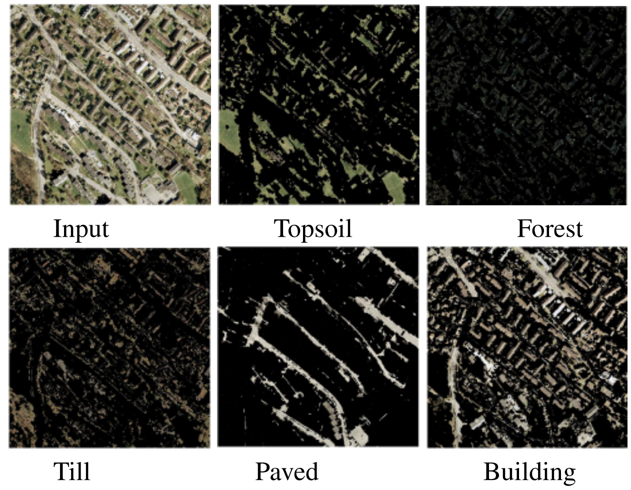



**Fig. 4**. An example tile from the dataset illustrates that, when the imaged area is predominantly urban, the classification result will be less successful.

feature. The gradient filter is based on a Sobel filter. The reason for choosing this technique is that the intra-class image gradient of `till` is very large thus setting the filter threshold to zero we extract most of that class. The gradient of the class `paved` and `building` is very low so it is then found by default. When this result is combined with the colour and entropy classification the segmentation to pick out the man-made features we are interested in i.e. roads and buildings. This is shown in Figure 2.2.

### 2.4. Results and discussion

The described steps result in three normalised likelihood distributions, $p^f_{ij}(c|d_{ij})$, one per feature, $f$, for every pixel location $ij$ over 5 possible classes given the pixel value at (i,j), $d_{ij}$ The chosen class for pixel (i,j) is given by:

$$C_{ij} = \text{argmax} \prod_f p^f_{ij}(c|d_{ij}) \quad (1)$$

By comparing the segmentation to ground truth data it is clear the colour segmentation gives a good result in classifying the topsoil and overall land surface (72%). In contrast to colour, the entropy stage performs well in classifying the paved and building by increasing detection from 38% to 65% on average. This poorer rate is partly explained by the fact that buildings are non-uniform in colour compared to vegetation. As discussed, the gradient feature can classify `till` well. Therefore, the colour segmentation result is used as a base and the entropy segmentation result is used to re-label the `paved` and `building` classes. The gradient feature is used to detect misclassified buildings by removing the paved and topsoil (the till having already been removed). The final result is shown in Table 1. As can be seen the main difficulty is twofold: (a) the ambguity between paved and building regions and (b) the variation within the class of building. We highlight this in Figure 2.4 and discuss the relevance of this misclassification to hydrological modelling in the following section.

| Topsoil | Till | Forest | Paved | Building |
|---|---|---|---|---|
| 80 | 93 | 93 | 56 | 65 |

**Table 1**. Percentage classification for each class in the test dataset.

## 3. HYDROLOGICAL MODELLING

We are unable to discuss the full details of the distributed hydrological modelling approach used here. Suffice to say that in distributed process models the area being studied is divided into a grid or network of elements, and calculations are carried out in each element, with all parameters discretised over the element grid [8]. The elements can be linked to estimate water movement (surface and subsurface) between them. WetSpa Extension is a GIS-based distributed catchment model, developed at the Department of Hydrology and Hydraulic Engineering of Vrije Universiteit Brussel, Brussels, Belgium. It is based on the earlier WetSpa model, designed for the prediction of Water and Energy Transfer between Soil, Plants and Atmosphere, at a regional or catchment scale, with a fixed daily timescale [10]. Both the offical land use and the derived land use are shown in Figure 3. These are reclassified into the 5 classes and the rasters are used as input to the WetSpa model, implemented in ESRI ArcView 3.2 with the water balance and flow calculations implemented in FORTRAN. Despite the reclassification introducing further errors,

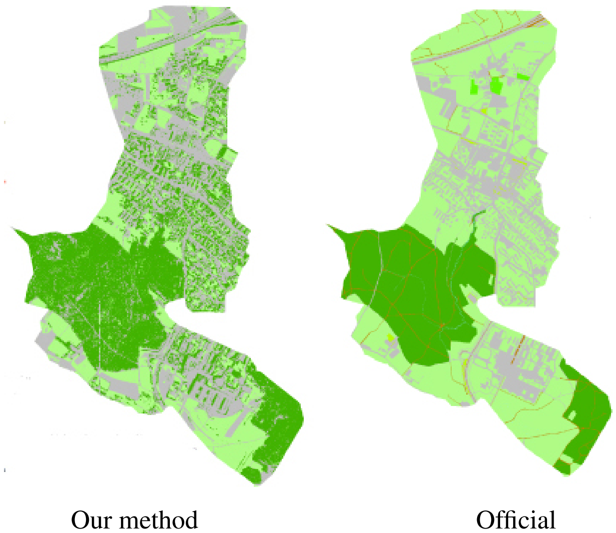



**Fig. 5**. Automatically-derived land use compared to the official land use supplied by City of Zurich showing the presented method over the entire dataset surrounding the river catchment of interest. The original classification has been reclassified into the 5 classes used in this paper.

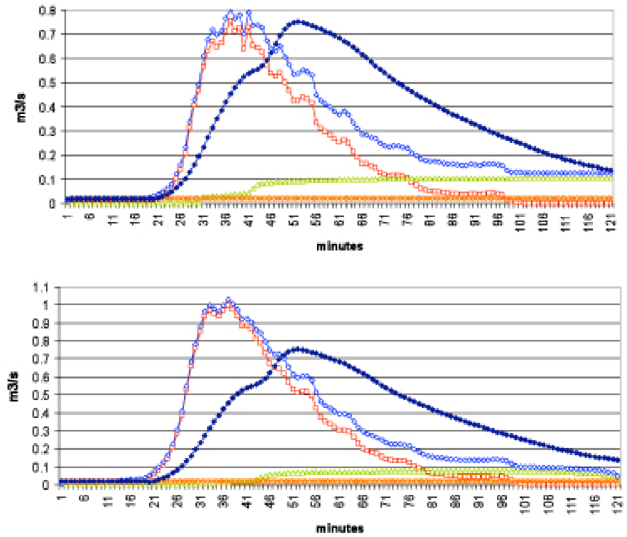



**Fig. 6**. The WetSpa model computed from the estimated flow (top) and from the official land use classification (bottom). Each graph shows estimated $m^3$ per second over a 60 minute period. The main peak on the left shows the total estimated flow.

about 70% of the pixels are correctly identified. As can be seen from Figure 3 we obtain a similar estimate of the peak flow (light blue curve) with the maximum flow being 20% higher than that computed using the official classification.

## 4. CONCLUSION AND FUTURE WORK

We have presented a method for image segmentation which has been applied to a large, real dataset of aerial images. We have further demonstrated the utility of our approach in a new approach to hydrological modelling, showing that despite the coarseness of the classification and the inevitable errors in the automatic technique, we achieve tolerable results compared to those computed using hand-labelled data. The segmentation method is clearly tailored to both the type of class we aim to detect and to the application. However, we have resisted heuristics such as shape recognition to improve the identification of specific buildings. This means that the presented method is a general approach to aerial image segmentation. Further refinements would take account of shadow and explore the expansion of the number of classes to improve the peak flow estimate.

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