TSBB11

CDIO 2015

CARTOMATIC

INTRODUCTION

With today's technology it is possible to get very high resolution satellite images of the earth. This data could be used to create accurate and up-to-date maps. Creating maps by hand is a very time consuming and challenging task. An automatic classification system that can create maps from satellite images would therefore facilitate this process.

The goal of this project was to automatically classify geographical structures such as roads and water in satellite images over Sydney, Australia, with the use of neural networks.

Vricon is an international company that develops realistic 3D models based on satellite images. OpenStreetMap (OSM) is an open source project that allows private users from all over the world to add geographic information and in this way together create maps.

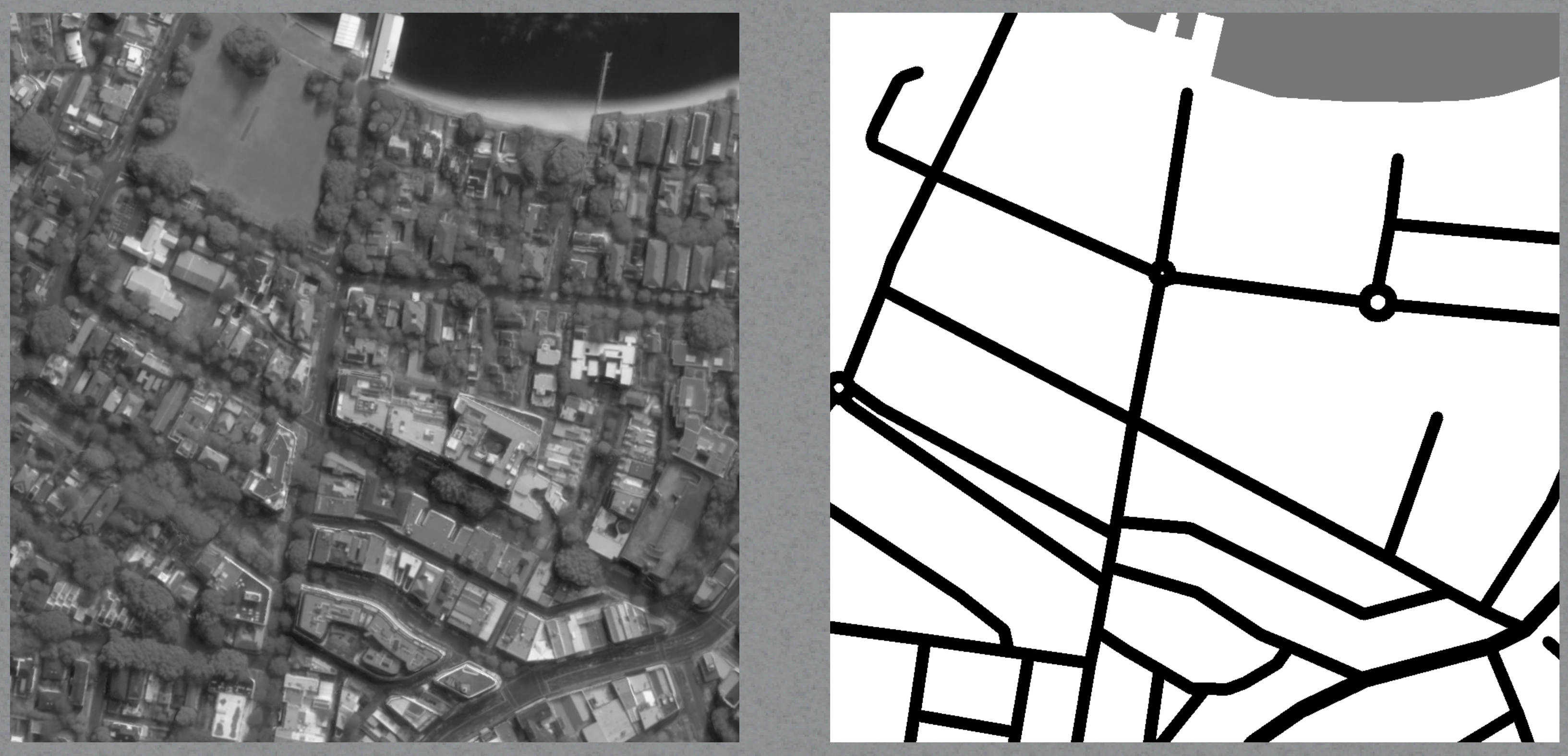

Figure 1: Example of satellite image cutout (left) with corresponding OSM ground truth (right). Black indicates road and gray indicates water.

SYSTEM OVERVIEW

The input data to the neural network consists of different features that are extracted from satellite images provided by Vricon. Ground truth data was generated from OSM, containing the relevant information (i.e. roads and water). After sufficient training, the network is tested on a different satellite image to generate a resulting classification and evaluate the systems accuracy.

Features were extracted by dividing the input image into small pixel blocks and calculating different measures that depend on the cocurences of pixel pairs. This was done for each color band (RGB, NIR and PAN). Figure 2 shows the features extracted from the green band that gave the best classification results.

A post-processing step is performed on the classification image in order to improve on the result further. The aim of this last step is to remove isolated pixels of classes that most likely are misclassified.

Figure 2: Features used in the system. ASM (UL), dissimilarity (UM), energy (UR), height threshold (LL), homogenity (LM) and mean (LR).

RESULTS

The confidence output from the network and post-processed classification max blended with the original for two test images are shown in Figure 3. Red represents background (BCC), green water (WCC) and blue roads (RCC). The accuracies for the classification max image (UL) were BCC: 73.3 % , WCC: 90.7 % and RCC: 73.1 %. After post-processing the accuracies were ramped up to BCC: 82.9 %, WCC: 94.5 % and RCC: 76.7 % (UR). The second test image contains no water and more distinct roads. The accuracies of the classification max were BCC: 76.4 % and RCC: 89.2 % (LL). The accuracies were ramped up to BCC: 85.6 % and RCC: 96.4 % after post-processing (LR).

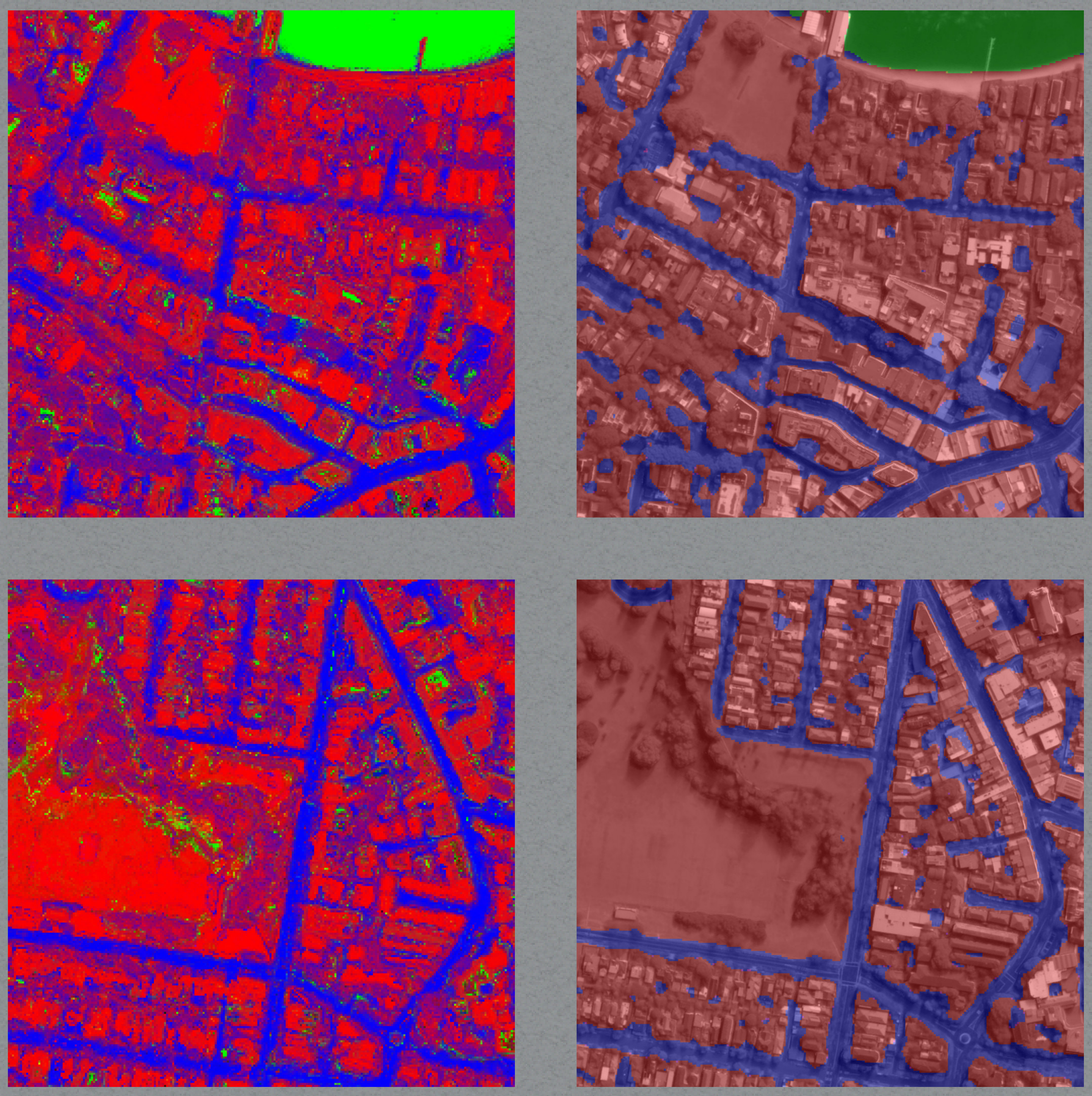

Figure 3: Classification confidence for two different test images (UL,UR). Post-processed classification max blended with original image (LL,LR).