TRACKING WATER COURSES IN SATELLITE IMAGES

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Abstract. We present an approach for tracking water courses in satellite images, a general strategy for tracking and recognising features in computer vision tasks on satellite images. Our approach is related to recent work in automatic image interpretation and urban scene analysis. We report a method for image recognition from multi-spectral SPOT satellite imagery, based on the different response of water to SPOT sensors. By this mean, we decide what regions are probably containing water. The problem of segmentation is solved by the “maximum entropy criterion” method, followed by a recognition task based on morphological properties of water courses. Some additional image processing techniques are required before obtaining the final water course mask.

Key-Words: computer vision, scene analysis, image segmentation, SPOT satellite images

1. INTRODUCTION

In automatic interpretation and scene analysis applications, tracking features such as roads, lakes, rivers, buildings or cars is sometimes a difficult and computing expensive task [1]. For purposes of automatic cartography or automatic navigation a quick an precise recognition algorithm is needed. The present paper describe a general framework for water courses detection based on the SPOT satellite XS3 images. We have based our work on this type of images for certain motivations, described in section 2.

Our approach combine image processing techniques such as histogram smoothing and image thresholding with feature recognition algorithm based on morphological properties. We found that entropy criterion can be applied to threshold methods with improved results. The mathematical background is shown in section 4. We also derived an “intuitive” algorithm for recognising water courses reported in section 5. Finally, in section 6, we present the software application that implements our framework and show images captured along the entire process. We also conclude on further improvements needed for including this method in automatic cartography applications.

2. SPOT IMAGES

The choice of SPOT satellite XS3 images is due to the optimal water response of SPOT sensors for tracking purposes. On infra-red spectrum, water appears in darken grey levels than other ground elements. If images were captured using thermal infra-red sensors, we could base our tracking on fact that water temperature in certain period of time (during the morning or in winter) is lower than the soil. And so, water course will appear in dark levels. Using XS3 images (near infra-red, 0.79 - 0.90 μm), water temperature would not be a valid detection criterion. Recalling that water molecule is absorbing almost all infra-red spectrum, a weak radiation will be reflected to sensor and cause dark grey levels. Note the dark colour of the water in figure 1. that shows the SPOT image of Seville located in Spain. All SPOT images have a ground resolution of 20x20 m per pixel and a ground dimension of 60x60 km [2].

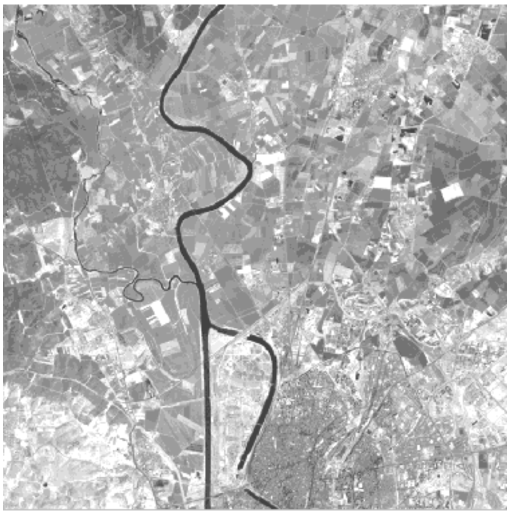

Fig.1. SPOT XS3 image of the city of Seville in Spain.

3. THE FRAMEWORK

In satellite images, a river or any other water course can be modelled as an object with a certain type of morphological properties. Intuitively, we realise that our goal object to detect must be “long and thin” and at the same time large, in comparison with other features presents in the image. A river is always the biggest uniform spot of colour present in infra-red satellite images, due to small ground dimensions of other objects (roads, buildings, crops).

Our “tricky” choice of the near infra-red SPOT image offers, for further processing, emphasised all water areas present in the given location. By this way, we have made easier all our recognition efforts.

Based on these assumptions, our framework will have the following steps:

1. pre-processing
   - a greyscale transform of the image if needed
   - a histogram smoothing or any other smoothing filter
2. threshold
   - thresholding the image, by fixing the level such as target object will be emphasised
3. recognition
   - “noise” cleaning
   - based on morphological properties, extract all object that match

In the following section, we will describe our implementation of step 2 and 3. The first one uses common image processing techniques and will not be discussed here.

4. THRESHOLDING

4.1. Threshold methods

In image processing tasks, object extraction from background is frequently the most important and difficult operation to perform. Identification and extraction of homogenous regions are accomplished by thresholding, with two approaches: - parametric methods and non-parametric methods. The first approach is computationally expensive and frequently, the results are poor. In the second one, thresholds are selected optimally following a given criterion and the method is more precise and robust. However, the weakness of this approach is determined by the classification number (number of grey level classes) who is often hard to obtain (user specified) or by the multi-level thresholding who is computationally expensive [3]. Studies accomplished on several threshold methods where leading on the Maximum Entropy Criterion (MEC) [4], described on the next section.

4.2. Maximum Entropy Criterion (MEC)

In order to formulate mathematical rules for the MEC, we firsts consider $f(x,y)$, an image of dimension NxN pixels and m grey levels. Assume $G_m=\{0,1,...,(m-1)\}$ the grey levels and $f_i \in G_m$ the appearance frequency of the grey levels in image f. The probability of level i in image f, will be:

$$p_i = \frac{f_i}{N \times N}, \quad i \in G_m$$

Thus, we obtain the $\{p_i \mid i \in G_m\}$ distribution. For a given s grey level, if $0 < \sum_{i=0}^{s-1} p_i < 1$, the next two distributions may be derived from this one, after a normalisation:

$$A = \left\{ \frac{p_0}{P(s)}, \frac{p_1}{P(s)}, \dots, \frac{p_{s-1}}{P(s)} \right\}$$

$$B = \left\{ \frac{p_s}{1-P(s)}, \frac{p_{s+1}}{1-P(s)}, \dots, \frac{p_{m-1}}{1-P(s)} \right\}$$

where $P(s) = \sum_{i=0}^{s-1} p_i$ is the total probability till (s-1) grey level.

The base idea of the MEC method is the appropriate choice of threshold that maximise the amount of information obtained from the object and background. Recalling that the measure of information is the entropy, the total amount of information given by A and B is:

$$TE(s) = E_A(s) + E_B(s) = -\sum_{i=0}^{s-1} \left(\frac{p_i}{P(s)} \right) ln \left(\frac{p_i}{P(s)} \right) = -\sum_{i=s}^{m-1} \left(\frac{p_i}{1-P(s)} \right) ln \left(\frac{p_i}{1-P(s)} \right)$$

$$= ln\left[P(s)(1-P(s)) \right] - \frac{H(s)}{P(s)} - \frac{H'(s)}{1-P(s)}$$

where: $P(s) = \sum_{i=0}^{s-1} p_i \qquad H(s) = -\sum_{i=0}^{s-1} p_i \cdot ln(p_i) \qquad H'(s) = -\sum_{i=s}^{m-1} p_i \cdot ln(p_i)$

The maximum entropy criterion assumes finding the threshold s' that maximise the following measure:

$$TE(s') = \max_{s \in G_m} TE(s)$$

The method is computationally feasible and leads in short time to the solution. Also, thresholds are determined automatically. Figure 2 presents the near infra-red SPOT image of town Freiburg located in Germany. Resulting image from automatic MEC threshold method is shown in figure 3.

Fig.2. Original image of Freiburg-Germany

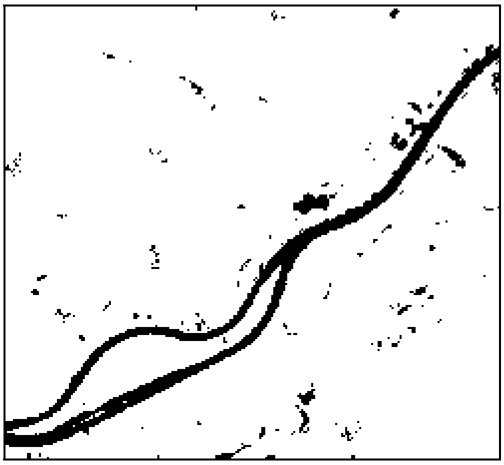

Fig.3. Output of the MEC threshold method

5. RECOGNITION

The thresholds processing method lead to a mask of darken zones without any distinction between water courses and noise or other water areas (lakes, swamps). The noise cleaning is made by erasing all pixel groups that fit in a 5 pixel width square. Areas greater than this empirically determined measure are candidate to recognition by morphological methods.

The algorithm is searching and marking every zone of the processed image. Basically, we can mark 254 distinctive areas, but practically only a few dozens are necessary. During a top-to-bottom scanning, the algorithm searches for a zone of black pixels, resulted from the threshold.

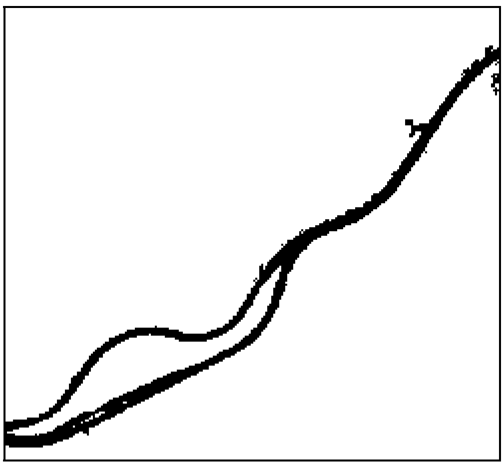

Fig.4. Output of the first recognition step

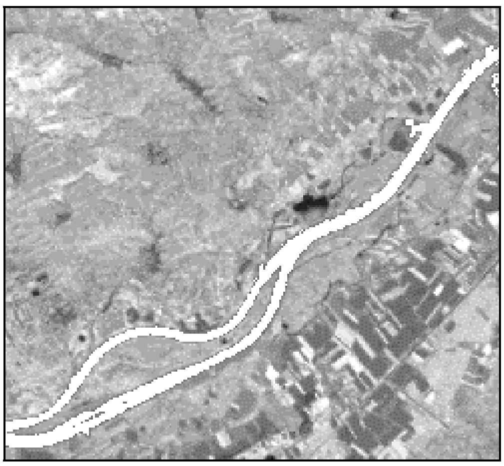

Fig.5. Output of the second recognition step

In parallel, it computes the area of the selected zone and decides if this measure match with a pre-selected range of areas. If it is too small, the zone will be erased. If not, a grey level will be conferred to all of its pixels. At the end of this processing step, we have transformed the binary image in an artificial grey image with all possible candidates to detection, as shown in figure 4.

Finally, we are again seeking the image, from top-to-bottom, for extracting morphological measures of all zones by the mean of polygonal approximation. If the ratio of the two best fit polygon diagonals are in a certain range, the recognition algorithm decides that a water course is present. Detected zones will appear on the final image within a blue mask as presented in picture 5.

6. CONCLUSIONS

All the results shown in this paper are obtained by implementing the described framework in one software application. The same software was used to test several algorithms and methods in order to select the best combination by generating images after each processing step. Testing the software supposed a large number of images that would contain water courses. Unfortunately only a few images could be acquired, but good and promising results where obtained. Figure 6 and 7 shows other two samples.

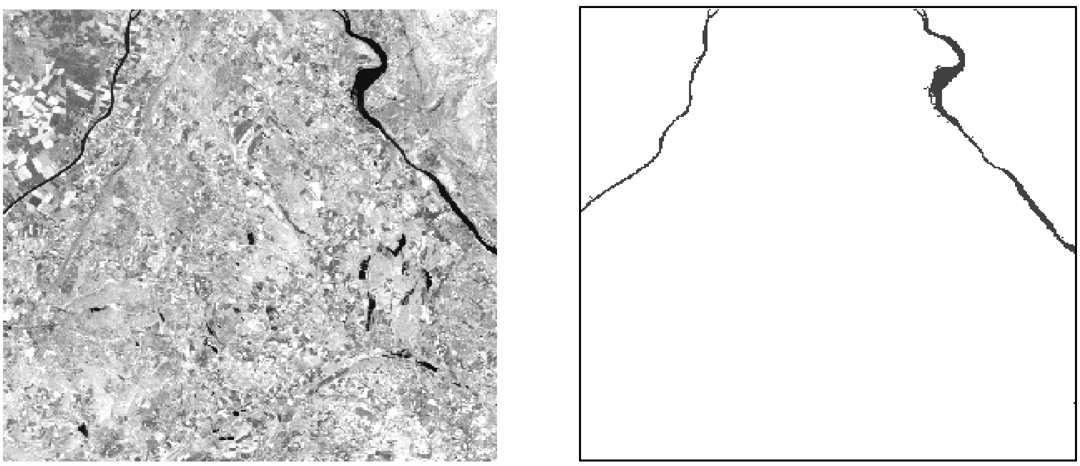

Fig.6. Original SPOT image and resulting water course mask

The method has several limitations due to the presence of small rivers that flow into large ones and the insufficient image resolution for representing them. If the river width is under a pixel or two, during recognition, the algorithm will fail to detect the object. This can be observed on figure 6. Also, the presence of bridges or underground channels could lead to false or non recognition. Every bridge will segment the water course in small items. If the resulting objects are to small, the algorithm will erase them. The same problem appears if several bridges are successively crossing the course. For further improvement of the framework, we consider developing an algorithm for automatic detection of bridges.

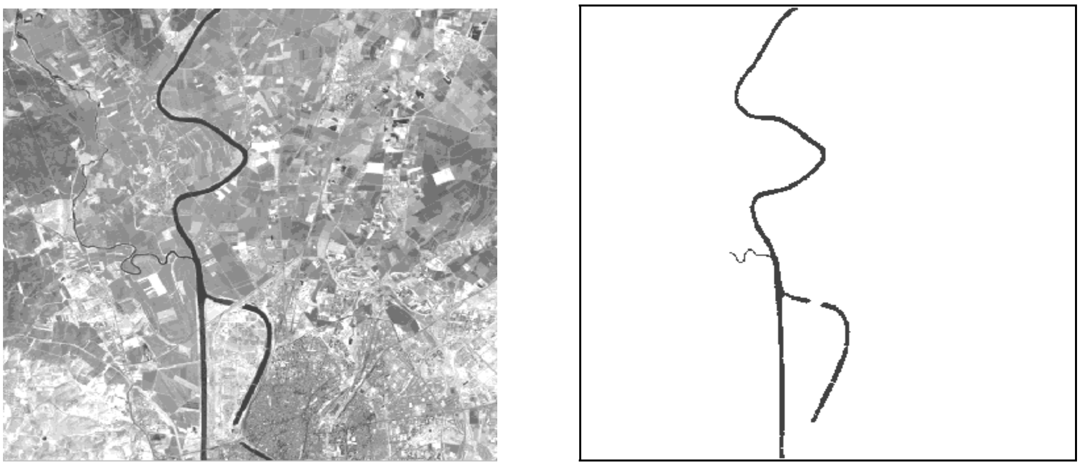

Fig.7. Original SPOT image and resulting water course mask. Notice limitations due to the presence of bridges and underground channels.

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