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Distinction of lakes and rivers on satellite images using mathematical morphology

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Abstract. This paper concerns the application of mathematical morphology for object-oriented classification of satellite images. The example of distinguishing different bodies of water using the author-made algorithm will be presented. Different types of water bodies like lakes and rivers are easy to differentiate when visually interpreted. However, it is much more difficult to differentiate using a traditional, pixel-based classification process. Mathematical morphology operations, which take into account such important features of objects like shape and size, allow these two types of water bodies to be distinguished in object classification. The proposed algorithm allows one practically error-free classification. The results show, that mathematical morphology is a potent tool for object-oriented classification.
Keywords: mathematical morphology, remote sensing, classification, contextual classification

1. Introduction

Water as a land cover class is very easy to determine through both visual interpretation on satellite images, and traditional, pixel-based classification processes, because of a very low reflectance, especially in the near and middle infrared part of the spectrum. This is what differentiates water pixels from non-water pixels. However, the distinction between different types of water bodies like lakes and rivers is easy only through a process of visual interpretation. Such a distinction might be important from the point of view of building geographic and topographic data bases at different levels of detail. E.g. in Poland it might be General Geographic Database (*Baza Danych Ogólnogeograficznych*) — level of detail at level of map in scale 1:250 000, V-map Level 2 in scale 1:50 000 (used for civilian and also military purposes) or Database of Topographic Objects (*Baza Danych Obiektów Topograficznych*) in scale 1:10 000.

Pixel-based classification, widely used in satellite image processing, seems useless for this purpose. The reason lies in the types of features being taken into account in these two different approaches. In the traditional classification, only digital numbers of pixels are taken into account, while during visual interpretation one additionally considers size, shape, neighborhood and other features of the object. For differentiation between lakes and rivers, possible thanks to identification of some object features like length and width (impossible in pixel-based classification process), the author proposes an automatic mathematical morphology-based algorithm.

Mathematical morphology is a powerful tool which can be used for changing the structure of an image depending on shape, size, neighborhood or other features of the objects contained within. In accordance to some simple presumptions relating to differences in shape of lakes and rivers, helping us distinguish them in visual interpretation, a sequence of morphological operations was developed. A preliminary step of the algorithm is creating of a water mask by extraction of water pixels in pixel-based classification (as mentioned before, this is a practically error-free process) or simple tresholding. Then, morphological operations, when properly applied, can eliminate objects (using the aforementioned presumptions) from the mask and distinguish different types of water bodies this way.

In this paper, the algorithm is circumstantiated, referring readers to the books and articles of mathematical morphology for an extended background to morphological operators. Then the algorithm is tested on 4 different satellite images (two Landsat ETM+ images, one SPOT 5 HRG image and one VHR image in natural colors, obtained using WMS from geoportal.gov.pl). The obtained results show a very high accuracy of the developed algorithm.

2. Mathematical morphology

Mathematical morphology is a set theory approach, developed by J.Serra and G. Matheron. It provides an approach to processing digital images based on geometrical shape.

Two fundamental morphological operations — erosion and dilation are based on Minkowski operations. There are two different types of notations for these operations: Serra/Matheron notation (Serra, 1982) and Haralick/Sternberg notation (Sternberg, 1986), (Haralick, 1987). They are, however, defined for binary images, and do not fit grey-scale image operations. Therefore we propose (after Nieniewski (1998)) a definition working for both: binary as well as grey-scale images. Erosion may be defined as follow:

$$\varepsilon_B(f) = \inf\{g(f-y), y \in B\},$$

where: is a structuring element,

so the result of an erosion is the smallest value amongst all images created by all offsets by the elements opposite to the elements of the structuring element.

In this notation, dilation may be defined as follows:

$$\delta_B(f) = \sup\{g(f+y), y \in B\}.$$

So the dilation is the highest value of all created by all offsets by the elements of the SE.

Two other principal operations, opening and closing, are simple sequences of erosion and dilation. Opening is defined by the following equation:

$$\gamma_B(f) = \delta_B(\varepsilon_B(f))$$

and closing as:

$$\varphi_B(f) = \varepsilon_B(\delta_B(f)).$$

Readers are referred to the books and articles of mathematical morphology for an extended background to morphological operators (especially hit and miss transformation (Serra, 1982, Jang and Chin, 1990) and the skeleton operator (Lantejoul, 1978, Ji and Piper, 1992), which are used but not presented in this paper, amongst others (Serra, 1988, Cheng and Venetsanopuolos, 1992, Nieniewski, 1998, 2005, Kupidura, 2006, Kupidura et al. 2010)).

3. The algorithm

The distinction between lakes and rivers in the visually interpreted algorithm is very easy thanks to unique colors (digital numbers) and the specific shapes of different types of water bodies. The traditional non-contextual pixel-based classification allows only the extraction of water pixels from the image, for there is no possibility of taking into account characteristics other than pixel value in such a process. That is the reason for developing the following algorithm based on mathematical morphology operators.

A fundamental aspect for the creation of the algorithm is the definition of the characteristics allowing distinction between lakes and rivers. We can thus define a river as a long and relatively thin water body, whilst defining a lake as a water body not fitting this description. According to this simple presumption we can now define the algorithm for extraction of river pixels from a water mask. After labelling rivers, the simple subtraction from the water mask of river masks could create a lake mask.

Below, the algorithm of the extraction of different types of water bodies is presented, also using an example of a part of a satellite ETM+ scene (fig. 1).

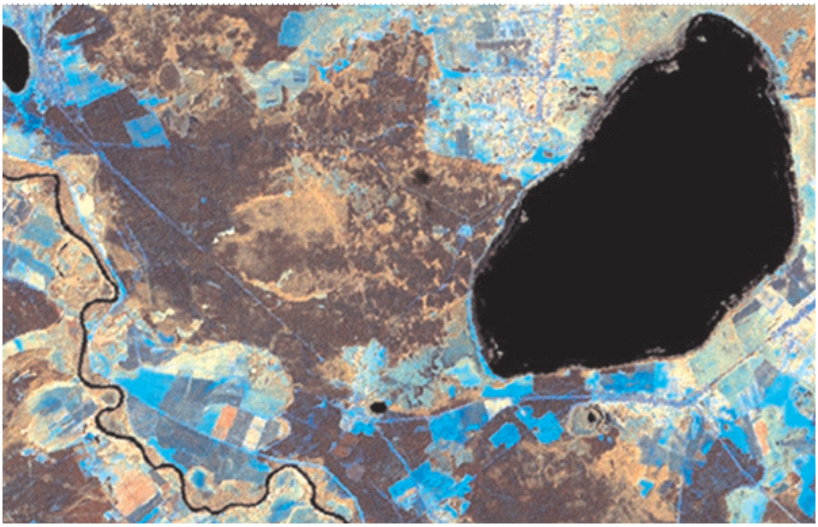

Fig. 1. Part of a satellite Landsat ETM+ scene (RGB 453)

Firstly, an obvious, in some point, version of an algorithm, based only on relatively simple utilization of contextual features of morphological operations is presented. As it will be shown later, this algorithm is not resistant to some specific kinds of water bodies, like e.g. lakes with islands. The improved version will be presented

1. **Water mask extraction**. It may be achieved by application of traditional non-contextual operations, like pixel-base classification or even simple tresholding, as water is usually represented by pixels of the lowest value in an image.
2. **Determination of the length of water objects**. Skeletonization of the water mask — the operation of skeletonization creates a one-pixel-thin axis (skeleton) of the object in the image, so a number of pixels in the skeleton of the object represents, more or less, the length of the object.
3. **Elimination of relatively short objects**. Application of pruning, operation allowing the identification and elimination of the end-points of the skeleton. After applying a specified number of iterations of this operation it removes completely the skeletons shorter than a specified length (number of iterations).
4. **Reconstruction of long objects — extraction of rivers**. Operation of geodesic reconstruction by dilation requires two images: a marker and a mask. Only these objects on the mask which are identified by the marker (i.e. some objects — non-zero pixels appear in the place of the object in the mask) are reconstructed. In this way, the mask of rivers can be created.
5. **Extraction of lakes**. It is achieved by simple subtraction of the mask of rivers from the general mask of water bodies.

Such an approach is, as it is written before, quite obvious and can be found in other papers (e.g. Candeias, 1997). Alas, this algorithm can be ineffective for a small number of reasons. First of all, large lakes may appear in the image, so their skeletons could be comparable to the skeletons of some rivers, especially when the images of the rivers are broken due to low spatial resolution of the satellite image. The second problem can be caused by islands. In the situation where an island appears in a lake, its skeleton is represented not by a line but by a loop without any end-points, so it cannot be eliminated in the pruning operations, no matter how many iterations are applied (fig. 2), so the distinction between lakes and rivers might be erroneous, as some of lakes (those with islands) might be counted as rivers, as their skeletons would not be eliminated in step 3.

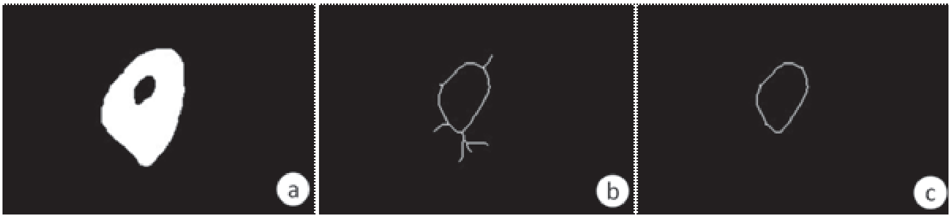

Fig. 2. a) test image; b) skeleton if image a; c) skeleton after an "infinite" (in this case — 16) iterations of pruning

To avoid errors of this type, an improvement of the algorithm is needed. Thus, to resolve the first problem, we need to check not only the lengths of the objects but also their widths — every object wider than a specified dimension can be eliminated from the rivers mask using a white top hat transformation, allowing to eliminate big objects (comparing to the size of the structuring element). Another problem caused by islands can be resolved by applying close-hole operations (Angulo and Flandrin, 2003) to fill the holes in the water mask and avoid loops created in these places (fig. 3 presents the result of skeletonization and pruning applied on an image a) from fig. 2, but with a close-hole operation processed previously)

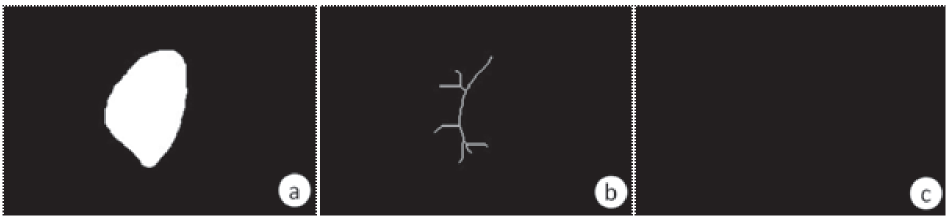

Fig. 3. a) test image (fig. 2 a) after close-hole operation; b) skeleton of the image a; c) skeleton after an "infinite" (in this case — 25) iterations of pruning

Additionally, some typical classification errors may appear. As water class is relatively easy to extract in an image.

The final algorithm, taking into account the above, is as follows:

1. **Water mask extraction** — traditional classification or tresholding.
2. **Elimination of isolated, incorrectly classified pixels** (water as well as non-water) — by using an alternate filtration by reconstruction it is possible to eliminate small objects (or holes in objects) without changing the general size and shape of the objects (fig. 4).

Fig. 4. Filtered water mask

3. **Elimination of wide objects** — wider than the dimension of the structuring element, by using WTH (white top hat) transformation using a big structuring element (fig. 5).

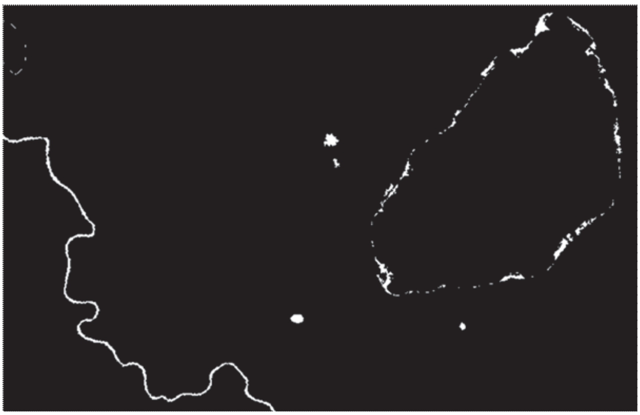

Fig. 5. Application of WTH transformation. All the big objects are removed (except for some parts of them)

4. **Elimination of holes** potentially causing loops in the skeletons of the objects by using a close-hole operation.
5. **Determination of the length of water objects** — a skeletonization creating a one-pixel-thin axis (skeleton) of the object in the image, representing the length of the object (fig. 6).

Fig. 6. Skeletons of objects. As one can see, skeletons of short objects are obviously shorter

6. **Elimination of relatively short objects —** pruning — the elimination of skeletons shorter than a specified length, determined by a number of iterations of pruning (fig. 7).

Fig. 7. Skeletons after pruning (50 iterations). All short skeletons are completely removed from the image

7. **Creation of the marker for geodesic reconstruction** by dilation. As a marker for geodesic reconstruction must be not bigger than a mask (i.e. every

pixel in a marker image must have not higher value, than the adequate pixel in a mask image), further process requires a calculation of a logical product of initial water mask and the result of pruning. This step is necessary, because the pruning process is applied on a skeleton of a "hole-closed" image, so some parts of skeletons might appear in "holes", i.e. islands.

8. **Creation of rivers mask**. Geodesic reconstruction by dilation of initial water mask from the marker created in a step 7 — water mask is reconstructed only where the marker indicates the appearance of the objects long and thin enough to be the rivers other water bodies have been eliminated during processes of WTH transformation and skeletons pruning (fig. 8).

Fig. 8. Reconstruction of river mask from the pruning result

9. **Creation of lakes mask**. Subtraction of rivers mask from initial (or filtered) water mask (fig. 9).

Fig. 9. Lakes mask

This algorithm works well in the case of most images. However, for some images, especially images of big cities this algorithm may be insufficient because of the broken images of rivers. Rivers in such cities are often very wide, which combined with their images being broken by images of bridges, can cause some uncertainty in classification of the type of object. To resolve this problem, the following development of the algorithm may be applied, just after step 1 (extraction of the water mask) of the algorithm presented above:

a) closing small gaps caused by bridges, between parts of the water mask — closing operation using a relatively small structuring element for,
b) creation of a mask of non-water and non-bridge (non-road) pixels — by a classification process,
c) subtraction of the results of steps a) and b) — removing of the "unentitled" connections made during the closing operation, where any bridge (road) does not exist. Thanks to this operation, the risk of connecting different water bodies is minimized.

Figure 10 presents the results of the algorithm presented above.

In the next section the accuracy of both algorithms: basic and extended is tested.

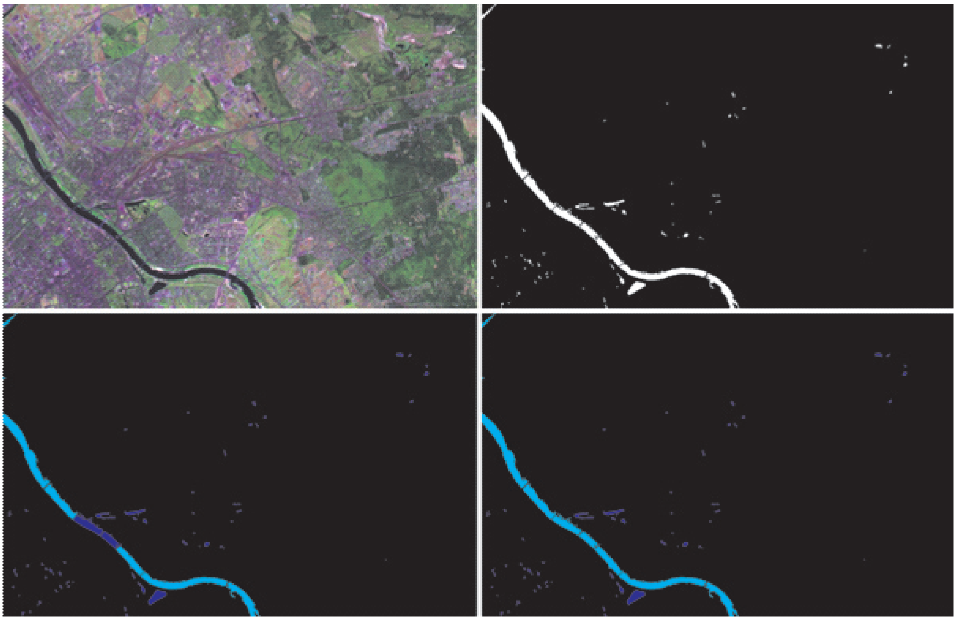

Fig. 10. a) fragment of a SPOT 5 satellite scene (RGB 432); b) water mask; c) the result of an application of the original algorithm (cyan — rivers, blue — lakes); d) the result of an application of the extended version of the algorithm (cyan — rivers, blue — lakes)

4. Results

The algorithm has been tested on 4 different satellite images (ETM+, SPOT 5 HRG and VHR natural color composition). The results of visual interpretation of the image have been treated as a reference data for the testing. On figure 11, the results of the application of the algorithm on all test areas are presented.

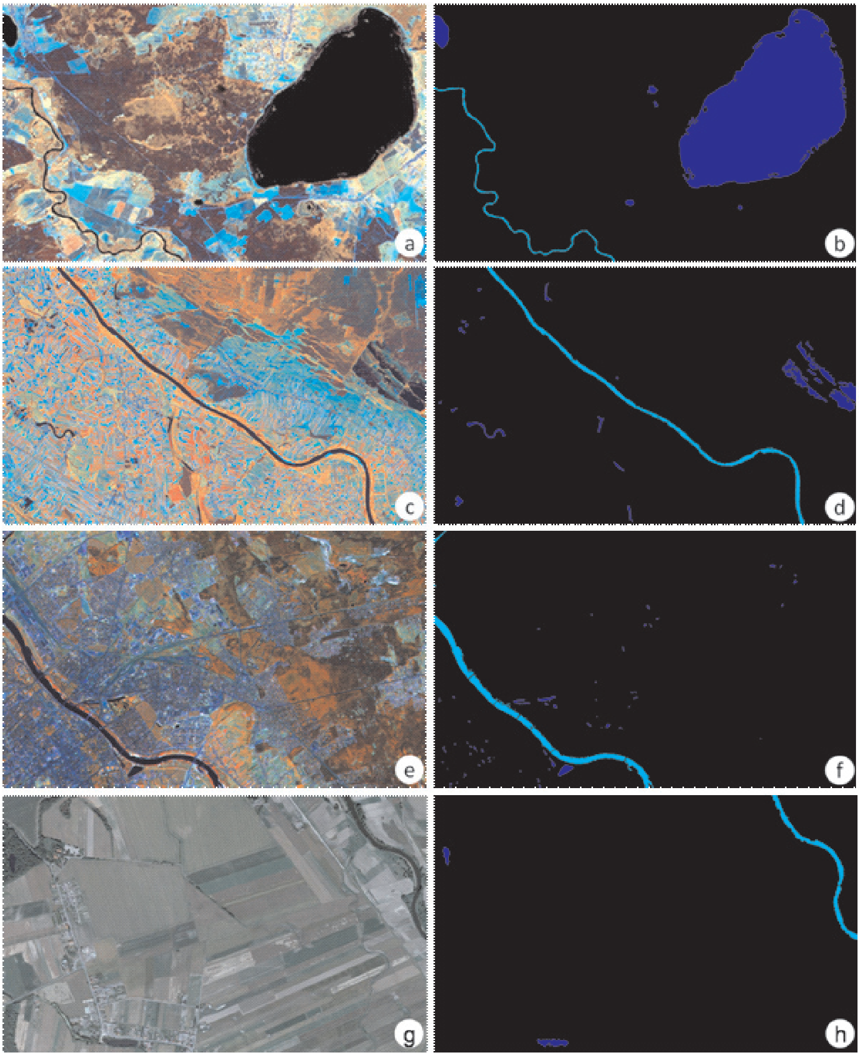

Fig. 11 a) Test image 1; b) test image 1 classification result; c) Test image 2; d) test image 2 classification result; e) Test image 3; f) test image 3 classification result; g) Test image 4; h) test image 4 classification result

Tables 1-4 show the values of the Cohen's kappa coefficient obtained for 4 test images. Cohen's kappa coefficient is a statistical measure of agreement (Carletta, 1996). Only two water classes (lakes and rivers) have been included for the accuracy assessment. As a possible cappa value varies from -1 (total disagreement) and 1 (total agreement) (0 in this case means, that an accuracy of the process is comparable to a random one), we may see, that the distinction between to types of water bodies is almost error-free.

Table 1

Accuracy of classification — test image 1

	Test image 1	Reference image: lakes [pixels]	Reference image: rivers [pixels]	commission error [%]
Result image	lakes [pixels]	113380	224	0.2
	rivers [pixels]	102	8534	1.2
	omission error [%]	0.1	2.6	**kappa: 0.98**

Table 2

Accuracy of classification — test image 2

	Test image 2	Reference image: lakes [pixels]	Reference image: rivers [pixels]	commission error [%]
Result image	lakes [pixels]	3801	24	0.6
	rivers [pixels]	31	4295	0.7
	omission error [%]	0.8	0.6	**kappa: 0.99**

Table 3

Accuracy of classification — test image 3

	Test image 3	Reference image: lakes [pixels]	Reference image: rivers [pixels]	commission error [%]
Result image	lakes [pixels]	6501	153	2.3
	rivers [pixels]	55	71735	0.1
	omission error [%]	0.8	0.2	**kappa: 0.98**

Table 4

Accuracy of classification — test image 4

	Test image 4	Reference image: lakes [pixels]	Reference image: rivers [pixels]	commission error [%]
Result image	lakes [pixels]	4128	0	0.0
	rivers [pixels]	0	15126	0.0
	omission error [%]	0.0	0.0	**kappa: 1.00**

We may claim, that the final accuracy of the presented process depends mainly on the accuracy of a water class extraction in the image.

5. Conclusions

The paper shows that the presented algorithm is an efficient tool for the distinction of different types of water bodies. All it needs to perform is a determination of two parameters — maximal width and minimal length of the rivers. Moreover, the paper shows the potential of the mathematical morphology operations for object-oriented classification of remote sensing data. By using relatively simple morphological operations, images can be processed in the far more advanced and accurate way than using traditional, pixel-based algorithms.

The very important advantage of the presented algorithm is that it can be performed using free software that can be downloaded via Internet.

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P. KUPIDURA

Rozróżnienie rzek i jezior na zdjęciach satelitarnych, przy użyciu morfologii matematycznej

Streszczenie. Artykuł dotyczy zastosowania morfologii matematycznej do obiektowej klasyfikacji treści zdjęć satelitarnych. Działanie wybranych operacji morfologicznych przedstawione jest na przykładzie autorskiego algorytmu, którego celem jest rozróżnienie różnych typów zbiorników wód powierzchniowych, takich jak jeziora i rzeki. Ponieważ takie rozróżnienie wymaga wzięcia pod uwagę takich cech obiektów, jak rozmiar, długość, czy szerokość, kształt, tradycyjna klasyfikacja pikselowa, oparta na wartościach pikseli, jest nieskuteczna. Operacje morfologii matematycznej, ze swojej natury kontekstualne, pozwalają uwzględnić wspomniane wcześniej cechy, co z kolei umożliwia odróżnienie obiektów na podstawie ich kształtu. Klasyfikacja dokonana przy użyciu autorskiego algorytmu na zdjęciach satelitarnych przedstawiających różnego rodzaju obszary testowe, została porównana z wynikami fotointerpretacji zdjęcia, uznanej za bezbłędną. Porównanie wskazuje na dużą skuteczność prezentowanego algorytmu, a jednocześnie, na duży potencjał operacji morfologicznych w zakresie obiektowej klasyfikacji zdjęć lotniczych i satelitarnych.
Słowa kluczowe: morfologia matematyczna, teledetekcja, klasyfikacja, klasyfikacja kontekstualna