

WEAKENED WATERSHED ASSEMBLY FOR REMOTE SENSING IMAGE SEGMENTATION AND CHANGE DETECTION

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Abstract: Marked watershed transform can be seen as a classification in which connected pixels are grouped into components included into the marks catchment basins. The weakened classifier assembly paradigm has shown its ability to give better results than its best member, while generalization and robustness to the noise present in the dataset is increased. We promote in this paper the use of the weakened watershed assembly for remote sensed image segmentation followed by a consensus (vote) of the segmentation results. This approach allows to, but is not restricted to, introduce previously existing borders (e.g. for the map update) in order to constraint the segmentation. We show how the method parameters influence the resulting segmentation and what are the choices the practitioner can make with respect to his problem. A validation of the obtained segmentation is done by comparing with a manual segmentation of the image.

1 INTRODUCTION

Region classification is becoming increasingly more used in the remote sensing applications as reviewed in (Carleer et al., 2005). The watershed transform is known to give an interesting solution for image segmentation by creating closed contours (Beucher and Lantuejoul, 1979). Watershed transform has been widely used in remote sensing image segmentation, its major benefits being an extreme sensitivity to detect borders and the outcome of closed contours which are useful for consecutive segmentation exploitation (Chen et al., 2004). Due to its extreme sensitivity, the use of the watershed transform may lead to the creation of many unwanted local watershed basins in a highly textured area. This problem increases dramatically with the image resolution available. Over-segmentation issue is usually tackled by three, possibly complementary, ways: (i.) image low pass or similar pre-filtering that eliminates local minima and therefore diminishes the number of unwanted watershed basins, (ii.) using the marked watershed transform to limit the basins to only those

which are marked and (iii.) by using a basin fusion step after the watershed transform. This step often integrates multi-spectral data that are available. As described by (Noyel et al., 2007), not all the borders present in the image are of interest. Indeed noise or very small structures cause local minima (in the gradient image) that give rise to small regions (i.e. over-segmentation). On the contrary, some borders are important and significant with respect to the tackled problem and exhibit more stability (e.g. to marker selection). Randomization of such learning can be done by modifying the marks (Noyel et al., 2007), but, similarly to the weak classifier paradigm, one can also influence the result of the watershed transform by modifying the data (i.e. the gradient image) itself. Recent developments have shown that watershed transform randomized by mean of random marks gives interesting results both in unsupervised (Noyel et al., 2007; Angulo and Jeulin, 2007) and supervised approach (Debeir et al., 2008). The way to limit the number of watershed basins is here linked to there stability to perturbations, only stable/robust borders are kept. A similar result can be obtained by introducing

noise inside the gradient image itself (Debeir et al., 2008). We will show here that a combination of random marks and gradient perturbation allows to tackle efficiently remote sensing image segmentation as pre-processing step to region classification. Moreover the proposed method allows to include a pre-existing border map in order to constrain the segmentation process as expected for the map update framework.

2 MATERIAL

The study area is situated in the southeast of Belgium, near the city of Arlon. The image data are panchromatic QuickBird images acquired in 1999 and 2004 with a resolution of 0.6 m. Borders of the panchromatic 2004 image are computed by a classical morphological filter of radius 1 (4 neighbors). The operation is achieved on the complete 11 bit panchromatic image dynamic. The obtained gradient is converted into 8 bit image (levels higher or equal to 255 are set to 255). Both images of 1999 and 2004 were manually segmented. Borders of 1999 labels are considered as a priori knowledge, indeed in the context of map update, the pre-existing map can be considered as known and serves as input to the image segmentation. The labels of 2004 will be used exclusively as validation and are not used during the segmentation. All images are considered as registered with respect to the smallest available detail. Label images are rasterized from the supervised label images of year 1999 and 2004. In order to put the borders between the labels, the image is oversampled two times in both dimensions. Other raster images are extended within the same proportions (nearest value).

3 METHOD

Numerous theoretical and experimental studies show that a combination of several diverging classifiers (also called multiple classifier system or ensemble approach) is an effective technique for reducing prediction errors (Kittler et al., 1998; Bay, 1998; Breiman, 1996). The key of this improvement relies greatly on the degree of decorrelation of the errors between the classifiers. One approach to create error diversity is to perturb input data in order to train the component classifiers with different training sets (weakened classifiers). We promote here the use of image perturbation and marker randomization in order to build the assembly of randomized segmentation based on marked watershed transform.

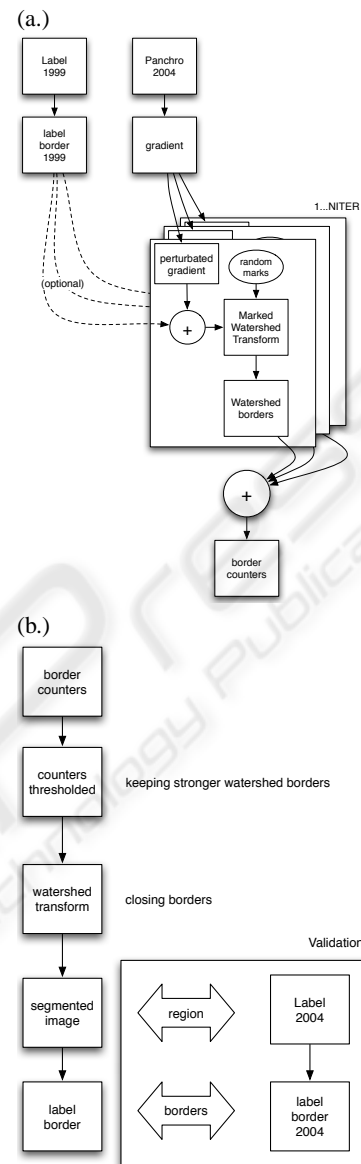


Figure 1: Ensemble approach: (a.) the counter image is generated by the assembly of randomized watershed transform (perturbated gradient and randomized marks), (b.) the obtained borders are compared with the supervision.

Figure 1 illustrates the overall segmentation process with (a.) the randomization phase and (b.) the consensus phase. The different steps are explained in the following paragraphs

3.1 Image Perturbation

A random slope (*SLOPE*) image based on random Fourier transform image is added to the gradient image of 2004 (the *SLOPE* is scaled to an interval of $[-MAXSLOPE, +MAXSLOPE]$). As result, some

weak gradient levels present in the original image can be reinforced, whereas others are smoothed. *SLOPE* image is generated by applying the inverse Fourier transform to a randomly generated frequency domain image. Let f be an empty image (imaginary) of size equal to the gradient image (image origin is centered). We add n pixels (here we arbitrarily used $n = 5$) of value $I+j$ for randomly generated positions as follows:

$$f(x,y) = \begin{cases} 1+j & \forall (x_k, y_k) = (\rho_k \cos(\theta_k), \rho_k \sin(\theta_k)) \\ 0 & \text{else} \end{cases} \quad (1)$$

where

$$\begin{aligned} \theta_k &= 2\pi U(0,1) \\ \rho_k &= 1 + f_{max} U(0,1) \\ k &= 1 \dots n \end{aligned} \quad (2)$$

The f_{max} parameters limits the upper bound of the spatial frequency injected in the *SLOPE*. It was set experimentally to 10. The *SLOPE* image is normalized in $[0, 1]$ using:

$$SLOPE = (\mathcal{F}^{-1}(f)) / \max(\mathcal{F}^{-1}(f)) \quad (3)$$

Figure 2 (a.) shows an example of a random *SLOPE* obtained. Due to the nature of the tackled problem (map update), one might be interested in adding existing borders to the segmentation (e.g. from an old labeled image of the same region). It is indeed common for an updated image to retrieve many borders from a previously remote sensed image. Of course some borders may also disappear, this case will be discussed further.

In order to inject this *a priori* knowledge, the existing borders of the 1999 label image are injected after the gradient perturbation. Each pixel of the 1999 image belonging to a label border is forced to the maximal gradient value (255). An example of a modified gradient image is illustrated in figure 2(b.).

3.2 Randomized Marked Watershed

Marker image is built by randomly (using a uniform distribution) marking pixels inside the image domain. The parameter *DENSITY* gives the number of marks generated per image pixel.

3.3 Watershed Assembly Consensus

NITER iterations of the modified gradient image and random marks are built. For each iteration, marked watershed transform is applied on the modified gradient image using random marks (one different gradient perturbation is computed for each iteration). This results in one segmentation as illustrated in figure 1(a.). The watershed basins borders obtained by each segmentation are accumulated into a *COUNTER* image.

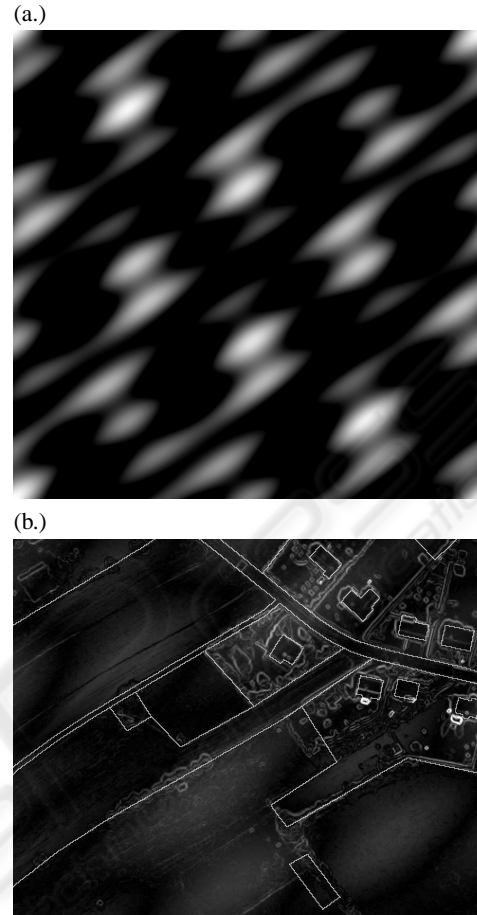


Figure 2: Gradient perturbation: (a.) random slope obtained by inverse Fourier transform (*SLOPE*) and (b.) *SLOPE* added to the 2004 gradient image (detail) with *a priori* (1999) borders in overlay.

The *COUNTER* image has high values for pixels frequently selected as watershed borders (i.e. robust borders), while low *COUNTER* values are pixels rarely involved in label separation. *COUNTER* pixels having a value greater than a selected threshold $COUNT_{th}$ value keep most robust border. In order to close the obtained borders, the watershed transform is applied to the thresholded *COUNTER* image as illustrated in 1(b.).

3.4 Segmentation Result Comparison

Region classification results depend greatly on the quality of the region used. We can identify two main defects for the segmentation: (i.) over-segmentation and (ii.) under-segmentation. If region borders overlap objects belonging to different classes (under-segmentation error), the classification process will perform poorly. On the contrary, if segmenta-

tion splits labels into numerous sub-regions (over-segmentation) one loses the benefit of using region rather than using pixels for the classification process. In order to assess the quality of obtained segmentation, we compare it with the manually obtained borders of the same image. We implement different image partition comparison coefficients described in the literature (Unnikrishnan and Hebert, 2005; Jiang et al., 2006). In (Unnikrishnan and Hebert, 2005), authors compare different kinds of methods (metrics) with respect to the application (e.g. same number of labels or not). If label images are C_1 and C_2 , one defines the Normalized Mutual Information (NMI) as:

$$NMI(C_1, C_2) = \sum_{c_i \in C_1} \sum_{c_j \in C_2} p(c_i, c_j) \log \frac{p(c_i, c_j)}{p(c_i)p(c_j)} \quad (4)$$

where $p(c_i, c_j)$ is the frequency of observing one pixel belonging to label i in C_1 and to label j in C_2 normalized by the total number of pixel in the image. Because changes are very subtle between the two available datasets (1999 and 2004) we extract an other measure more focused on label borders differences. Border changes are counted as $ADD_{rel}(C_1, C_2)$ pixels borders (i.e. border present in C_2 that is not a border in C_1) and $REM_{rel}(C_1, C_2)$ (i.e. border present in C_1 that is not a border in C_2) normalized by the number of image pixels.

4 APPLICATION

The map update framework can be stated as follows: we have a database containing the vectorial description of objects of interest at a certain moment (labels from 1999 represented in figure 3(a.)). A new image is acquired (e.g. by remote sensing) and registered to the database (the background image of the figure 3 (c.) and (d.) is the 2004 panchromatic image). The map update consists in creating a new label image (vectors) for the acquired image eventually using existing labels as support.

The randomized watershed assembly has been applied to the 2004 image and segmentation results were compared to the manual segmentation. Figure 3 shows an example of resulting segmentation.

In the given example, objects appear (+ sign), others disappear (- sign). The colors in figure 3 are used as follows : in (c.) the color overlay corresponds to the label (i.e. pre-existing) of year 1999 (i.e. same as (a.)), this corresponds to the *a priori* knowledge. In (d.) the color overlay corresponds to the 2004 label (i.e. same as (b.)) which is the updated version of 1999 label.

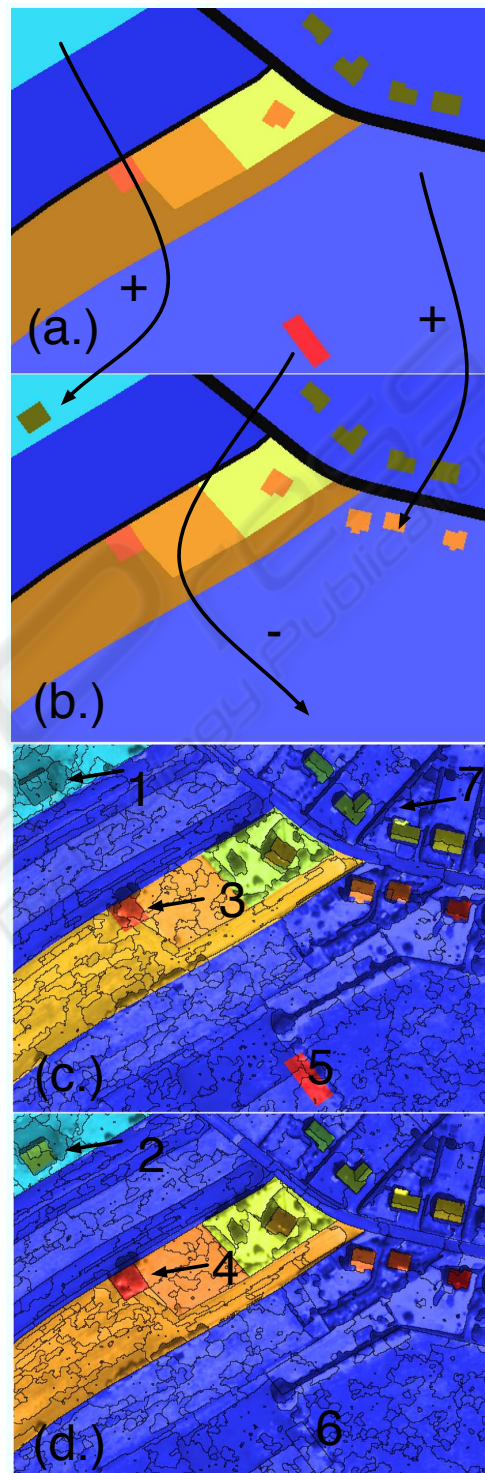


Figure 3: Segmentation results (detail): (a.) labels of 1999, (b.) labels of 2004, (c.) segmentation not using *a priori* knowledge (color overlay from the 1999 labels) and (d.) segmentation using *a priori* knowledge, i.e. borders of the 1999 labels (color overlay from the 2004 labels).

In the image (c.) the segmentation was done without using the *a priori* knowledge, one can see that watershed basins follow approximately the labels borders.

Using *a priori* knowledge (image (d.)) enhances the quality of these borders by forcing pre-existing borders (e.g. (3) and (4) in figure 3). Of course a label present in 1999 and not present in 2004 will create incorrect borders as illustrated by (5) and (6) in figure 3. For both approaches (with and without *a priori*) the method is able to segment thin structures (e.g. as illustrated by (7) in figure 3(c.)). New structures are well detected (e.g. (1) and (2) in figure 3 with and without using *a priori* knowledge. Man made structures such as houses and roads are well segmented (a small over-segmentation occurs on different roof slopes). Globally, all the objects are well detected in the sense that all object borders are included inside the segmentation for both methods using or not using *a priori* knowledge (pre-existing borders). Most labeled objects are over-segmented, as illustrated by (2) in figure 3, this is mainly due to the existing contrast (robust borders) inside objects of interest. Over-segmentation, if limited, would be addressed in a further classification scheme not illustrated here. The injection of *a priori* knowledge is well illustrated in figure 3 (d.), borders of object (4) are found by the segmentation procedure while randomized watershed assembly without using priors gives more irregular borders (object (3)). In the case of object that disappears from one image to the other (as illustrated by (6) where an object present in the database is missing in the new image), injection of *a priori* knowledge may generate false borders. This problem is also considered as over-segmentation and will be tackled in further classification steps.

5 PARAMETERS SETTINGS

As often the presented segmentation method relies on several parameters. Practitioner likes to have some rule of the thumb to have at least a starting point for the parameters setting. The method we propose requires the settings of basically four parameters : (i.) the marker density function (*DENSITY*), (ii.) the random slope (*MAXSLOPE*), (iii.) the number of voters (*NITER*) and (iv.) the threshold of the counter value (*COUNT_{th}*). We tested the variations observed on the results for a typical range for each of these parameters and summarized the results below.

Figure 4 (a.) shows how relative missed border evolves with respect to *COUNT_{th}*. The curve exhibits a minimum value around 10 on a total number of iterations equal to 35 which means that a border is to be

considered robust if its occurrence is higher than 1/3 of the total number of iterations. *DENSITY* of the random markers influences positively the number of segments as illustrated in figure 4 (b.) which is consistent with the marked watershed properties. Concerning the *MAXSLOPE* parameter, it is negatively linked with the number of *ADD_{rel}* borders (figure 4 (c.)), as well as with the number of segments (data not shown). This is coherent with the fact that small local gradient can be randomly smoothed by the *SLOPE* perturbation. The *COUNT_{th}* parameter tunes the level of over-segmentation, it can be easily set interactively by the user to select the segmentation granularity.

6 CONCLUSIONS

We propose the use of a weakened assembly of marked watershed transform for segmenting remote sensed imagery. This technique relies on the perturbation of the gradient image on one hand and on a random marking on the other hand. This approach also allows to take previously detected borders into account, which is useful when applied to map update. Different method parameters are identified and characterized with respect to the quality of the segmentation. Watershed randomization allows to detect small (thin) objects but also allows to limit the obtained segments only to the stable ones (i.e. limiting the over-segmentation). In comparison to manual labelling, the proposed method still gives more labels. However the obtained borders are consistent with the supervision, meaning that expected labels are well detected, but composed of few sub-labels. We show that under-segmentation is kept low by evaluating the missed borders. In this work, we do not use any spectral or contextual information. This will be considered in further automatic classification process.

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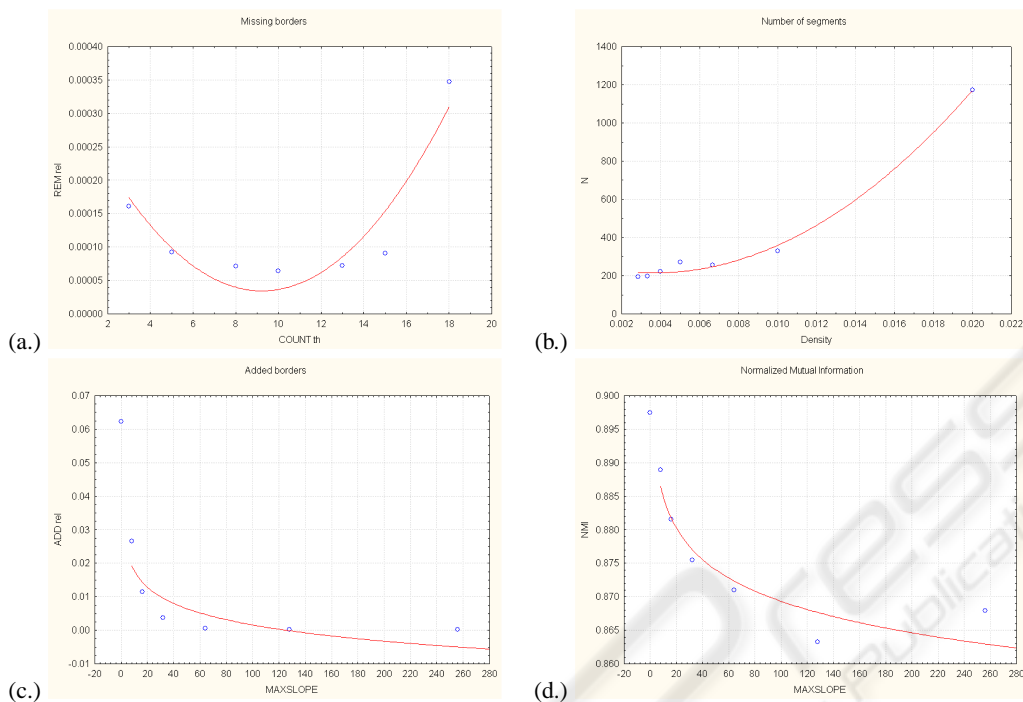


Figure 4: Method parameters influence: (a.) $REM_{rel}(C_1, C_2)$ vs $COUNT_{th}$, (b.) number of segment vs marker $DENSITY$, (c.) $ADD_{rel}(C_1, C_2)$ vs $MAXSLOPE$ and (d.) NMI vs $MAXSLOPE$.

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