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To cite this version:

Silvia Valero, Jocelyn Chanussot, Jon Atli Benediktsson, Hugues Talbot, Bjorn Waske. Advanced directional mathematical morphology for the detection of the road network in very high resolution remote sensing images. Pattern Recognition Letters, 2010, 31 (10), pp.1120-1127. 10.1016/j.patrec.2009.12.018 . hal-00578852

HAL Id: hal-00578852

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Submitted on 27 Mar 2011

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Advanced directional mathematical morphology for the detection of the road network in very high resolution remote sensing images

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Abstract

Very high spatial resolution (VHR) images allow to feature man-made structures such as roads and thus enable their accurate analysis. Geometrical characteristics can be extracted using mathematical morphology. However, the prior choice of a reference shape (structuring element) introduces a shape-bias. This paper presents a new method for extracting roads in Very High Resolution remotely sensed images based on advanced directional morphological operators. The proposed approach introduces the use of Path Openings and Path Closings in order to extract structural pixel information. These morphological operators remain flexible enough to fit rectilinear and slightly curved structures since they do not depend on the choice of a structural element shape. As a consequence, they outperform standard approaches using rotating rectangular structuring elements. The method consists in building a granulometry chain using Path Openings and Path Closing to construct Morphological Profiles. For each pixel, the Morphological Profile constitutes the feature vector on which our road extraction is based.

Key words: Road extraction, Mathematical Morphology, Path Openings and Closings, Morphological Profiles

1. Introduction

The new generation of satellites provides images with a very high spatial resolution, down to less than 1 meter per pixel. Featuring fine structures, this imagery can be used in a wide variety of applications such as mapping roads automatically. Until now, the automatic construction of road maps remains an important issue of research, since the need of human intervention is still required being by default expensive and time consuming. Furthermore, the geographical information about roads can be also used in urban mapping, urban planning and land management. Hence, fully automatic methods have been proposed to extract roads, railroads, drainage, and other meaningful curvilinear structures.

Unfortunately, the accuracy of the obtained results cannot satisfy the needs of some applications yet. The problems are generally associated to factors such as image resolution, image degradation or presence of non-road linear features in the image. Also, the poor visibility of the roads in the original image causes some limitations dividing one road into several short segments or completely missing it.

In general, proposed methodologies are based on road geometrical properties: roads appear as linear features in the image. A detailed review of the state of the art of road extraction methods can be found in [11] where some works are discussed and classified according to different aspects. For instance, a simple classification can be easily performed dividing road detection methods in fully automatic or semi-automic methods.
In semi-automatic approaches, algorithms uses some extra information such as seed points. In this field, Zhao et al [22] track initial linear seed points using template matching to determine the best direction of lines defining a road

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mask. Also starting from seed points, developed linear feature extraction methods using Active Contour models, called snakes, have been presented [10][7]. However, despite of the quality of these methods, they present limitations since they require initial seed points on each road central lines segments. Another important support in semi-automatic methods is GIS information. See for instance Guérin et al. [8] for pionnering work.

About common automatic methods, many works extract hypotheses for road segments through line and edge detections and then form a connection reconstruction between road segments to form road network [18] [20]. Many of these methods approximate the road network as a set of straight lines so the road accuracy suffers from this restricting assumption.

Mainly focusing on geometrical shape criterion, operators derived from mathematical morphology [14] have played an important role in automatic methods. For instance, Chanussot et al. [3] integrate morphological operators for selecting road regions. Mohammadzadeh et al. [12] uses these operators as a first step to propose a fuzzy algorithm. Also in Graud [5], a first line extraction achieved by these classical filters is used with Markovian Random Fields to extract road maps. Zang et al. [21] propose a granulometry analysis based on mathematical morphology for detecting roads.

In road extraction methodologies, the morphological filtering is used to remove the noise and unwanted features preserving roads segments as much as possible. However, the use of morphological filters in road detection suffers some limitations. Depending on the choice of a structuring element shape, they are not flexible enough to detect rectilinear and curved structures at the same time.

To remedy this limitation, different approaches are proposed in the analysis of oriented, thin, line-like objects. For instance, to detect brigth structures on a dark background the standard approach would be to use an infimum of openings using lines as structuring elements oriented in all the possible directions. The result is an isotropic operator if the line structuring element lengths are adjusted to be independent of the orientation.

In the same way, area and attributes openings have been studied for the analysis of thin structures. An area opening [19] of parameter λ is equivalent to the supremum of all the openings by connected structuring elements of area λ. Clearly, this includes all the straight line structuring elements of this length.

Practitioners often note that using only straight line structuring elements removes too much of the desired features, while using connected area or other known attribute operators does not allow them to distinguish between long and narrow features on the one hand, and short compact ones on the other. While it is sometimes possible to combine these operators to obtain the desired effect of retaining thin narrow structures while filtering out compact noise, this cannot always be done.

Recently efficient morphological operators using paths as structuring elements were proposed [17]. Paths are families of narrow, elongated, yet not necessarily perfectly straight structuring elements. These path operators constitute a useful alternative to operators using only straight lines and those using area or other attributes.

Fig. 1 summarizes the usefulness of path operators. In this example we wish to eliminate the compact round object and retain the line-like features. An area opening does not work in this case because the compact round noise is too big and one feature is eliminated before the noise as the parameter increases. Similarly the supremum of openings by lines suppresses features that are not perfectly straight. On the other hand the path opening delivers the expected result. Note that path openings do not afford control over the thickness of detected paths, both the thin wavy line and the thicker straight line are detected.

In the remainder of the paper, we propose to use these recently developed advanced directional morphological operators, namely path opening and path closing [17] to construct an automatic road map.
Our aim consists in exploiting the pixel local geometrical information provided by paths filtering results. For this purpose, we perform a granulometric approach using path openings and closing filters to construct Morphological Profiles vectors.

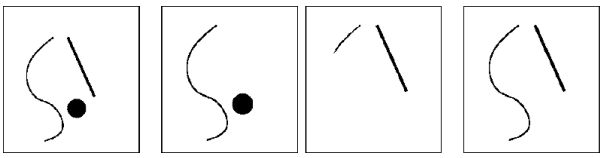


Figure 1: Example where we only wish to retain the line-like features while eliminating compact noise. Only the path opening works in this case.

Among the region analysis approaches, Morphological Profiles have been used for automated extraction of multi-scale urban features, such as buildings, shadows, roads, and other man-made objects [4][1][6]. For instance, Benediktsson et al.[2] applied classical morphological operators with different structuring element sizes to obtain Morphological Profiles containing structural information and then, they used neural network classifiers to label pixels according to their morphological profiles.
Here, we propose to analyze Morphological Profile constructed by Path Openings and Closings to extract the linear geometrical pixel information which allow to classify each pixel as road or non-road.

Figure 2 shows the flowchart depicting the overall methodology of the road extraction process. Firstly, a granulometric analysis using Path Openings and Closings is performed to construct Morphological Profiles vectors. Secondly, the extraction of linear geometrical pixel information from Morphological Profiles is performed. Finally, the road network is detected by a simple pixel classification according to the extracted feature.

The rest of the paper is organized as follows. Path Openings and Closings and Morphological Profiles are introduced in Section II. Section III describes the Morphological Profile analysis proposed to detect road network. Experimental results are discussed in Section IV ; and finally Section V is devoted to concluding remarks.

2. Morphological Profiles using Path Openings and Closings

In this section we recall the definition of path openings and closing, and we expand their use to include morphological profiles. In this and the following section, all definitions are given for the binary image space $\mathcal{P}(E)$. But the results can be generalised to the space of grey-scale images $\mathrm{Fun}(E, T)$ by means of the thresholding theorem for flat morphological operators [9, Chapter 11].

2.1. Path openings and closings

Let E be the image domain endowed with a binary *adjacency* relation $x \mapsto y$, meaning that that there is an edge going from x to y. In general, the relation '$\mapsto$' is non-symmetric, which means that the graph given by the vertices E and the adjacency relation $\mapsto$ is a *directed graph*. If $x \mapsto y$, we call y a successor of x and x a predecessor of y. Using the adjacency relation we can define a dilation on $\mathcal{P}(E)$ by writing

$$\delta(\{x\}) = \{y \in E \mid x \mapsto y\}\,.$$

In other words, the dilation of a subset $X \subseteq E$ comprises all points which have a predecessor in X. These concepts are illustrated in Fig. 3. Here b_1, b_2, b_3 are successors of a and $\delta(\{a\}) = \{b_1, b_2, b_3\}$. Furthermore, a_1, a_2, a_3 are the predecessors of b and $\breve{\delta}(\{b\}) = \{a_1, a_2, a_3\}$.

The L-tuple $\boldsymbol{a} = (a_1, a_2, \ldots, a_L)$ is called a *δ-path of length L* if $a_k \mapsto a_{k+1}$, or equivalently, if

$$a_{k+1} \in \delta(\{a_k\})\,, \text{ for } k = 1, 2, \ldots, L-1\,.$$

Note that $\boldsymbol{a} = (a_1, a_2, \ldots, a_L)$ is a δ-path of length L if and only if the reverse path $\breve{\boldsymbol{a}} = (a_L, a_{L-1}, \ldots, a_1)$ is a $\breve{\delta}$-path of length L. Given a path $\boldsymbol{a}$ in E, we denote by $\sigma(\boldsymbol{a})$ the set of its elements:

$$\sigma(a_1, a_2, \ldots, a_L) = \{a_1, a_2, \ldots, a_L\}\,.$$

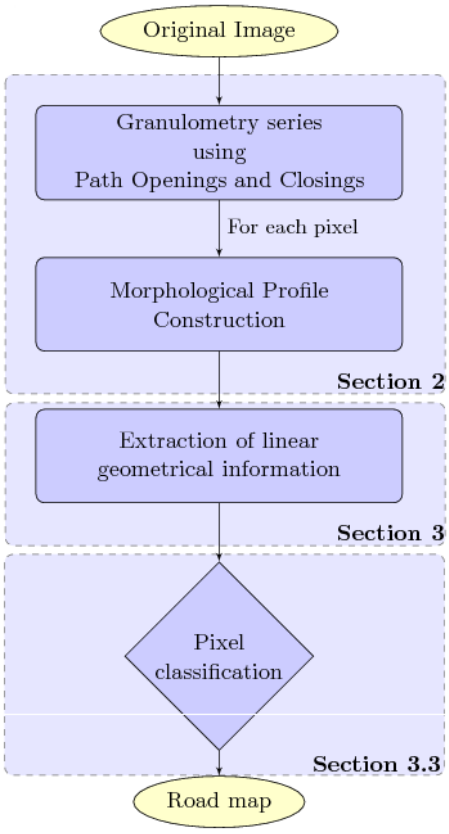


Figure 2: Flowchart describing Road Extraction Methodology

We denote the set of all δ-paths of length L by Π_L. The set of δ-paths of length L contained in a subset X of E is denoted by $\Pi_L(X)$, i.e.,

$$\Pi_L(X) = \{\boldsymbol{a} \in \Pi_L \mid \sigma(\boldsymbol{a}) \subseteq X\},$$

We define the operator $\alpha_L(X)$ as the union of all paths of length L contained in X:

$$\alpha_L(X) = \bigcup \{\sigma(\boldsymbol{a}) \mid \boldsymbol{a} \in \Pi_L(X)\}.$$

It is easy to see that α_L is an opening, and we call it the *path-opening*. Conversely, *path-closings* are defined by straightforward complementation (exchanging foreground and background). We illustrate the result of a simple path opening on Fig. 4.

Path openings and closings are dependent on the notion of graph connectivity. In order to be useful, this connectivity should reflect the kind of paths that the application requires. Examples of useful graphs are those that define cones oriented in the principal directions of the grid, as shown in Fig. 5. Path openings and closings in these graphs are those that retain paths that at each point fit in a 90 degree angle cone, oriented in a principal direction. Combination by supremum (for openings) and infimum (for closings) make it possible to retain paths oriented in all possible directions just using these four adjacencies.

Employed in this manner, path openings and closings can be used to retain features that are locally oriented but not necessarily perfectly straight. Path openings and closings can be implemented efficiently both in the binary and grey-level cases with a linear time complexity with respect to L using a decomposition algorithm [17].

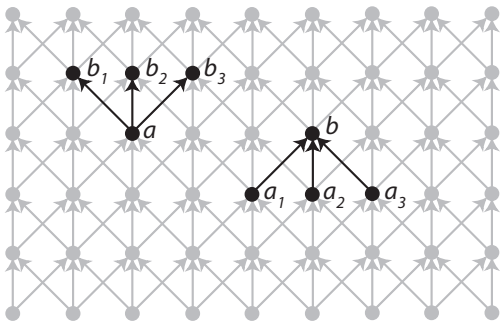


Figure 3: *b_1, b_2, b_3 are successors of a and a_1, a_2, a_3 are the predecessors of b.*

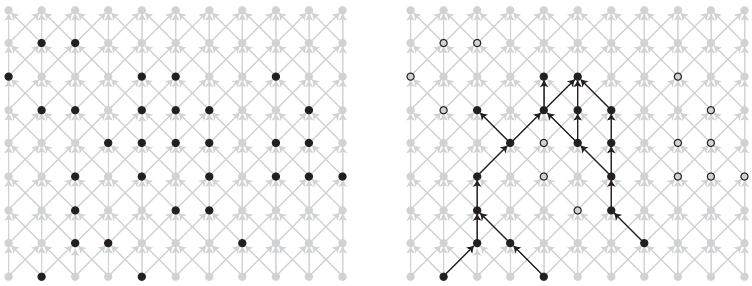


Figure 4: *A set $X \subseteq E$ (black points at the left) and its opening $\alpha_6(X)$ (black points at the right). Points at the right with thick boundaries have been discarded.*

2.2. Morphological profiles

In grey-levels, paths Openings and Closings retain oriented and locally linear structures that fulfill a minimal length L_{min} and that are respectively brighter or darker than their immediate surrounding. To perform this task, these filters assign to each pixel the highest (resp. lowest) gray level where a path fulfilling L_{min} is formed.

For these filters, the importance of setting the length L_{min} is similar to setting the observation scale of the results. In other words, L_{min} can be considered as the structuring element size for these morphological filters, while the shape remains flexible.

In our case, we use the adjacency graphs of Fig. 5, valid paths on such graphs are constrained at each of the path vertex to entirely fit in a 90° angle cone with one of four orientations. These are clearly oriented but not necessarily perfectly straight. It should be noted that in the following adjacency graphs shall be oriented out of necessity, as we will not allow paths to back down on themselves. Furthermore, note that on these graphs, exchanging the direction of the arrows would result in the same operation.

In the literature, the standard morphological approach for road detection consists in using narrow and elongated structuring elements and in testing them in all possible orientations [3]. Assuming the road appears as a dark feature on the picture, the *Supremum* of all the closings obtained by this rotating structuring element rotation removes all the dark features that do not fit the road model. The last step is a standard Top-Hat operator that enables the detection of the roads [3]. However, this method fails if the road is curved as illustrated on Fig. 6(b). No oriented rectangle fits inside the road, it is thus removed together with the other dark features. The roads are lost and will not be detected by the Top-Hat.
In order to overcome this problem, we propose to use Path Openings and Closings. Paths Operators can be interpreted

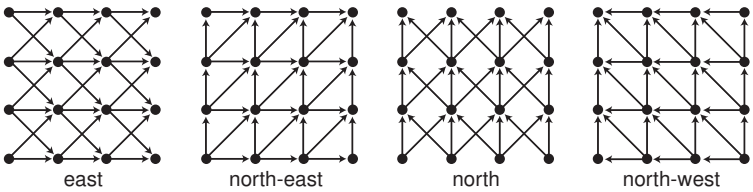
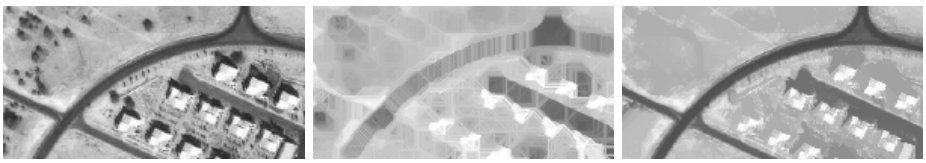


Figure 5: *Four different adjacencies.*

as standard operators using flexible structuring element of a given length. This flexibility makes it possible to fit in curved structures and, as a consequence, the road is not removed by the closing (See Fig. 6(c)), while other non elongated structures are actually removed. Then, the separation between the road and the other dark features is possible.



(a) (b) (c)

Figure 6: Comparison between standard and advanced directional morphological Filters. (a) Original Image; (b) Supremum of rectilinear Closings; (c) Path Closing

In our approach, we propose to use Path Openings and Closings to generate a multi-dimensional vector called Morphological Profile [2] for each pixel. To construct this vector, a serie of Path Openings and Closings with increasing L_{min} is successively applied to the image.

Then, noting $I(x, y)$ the original image, the Morphological Profile is computed for each pixel p as

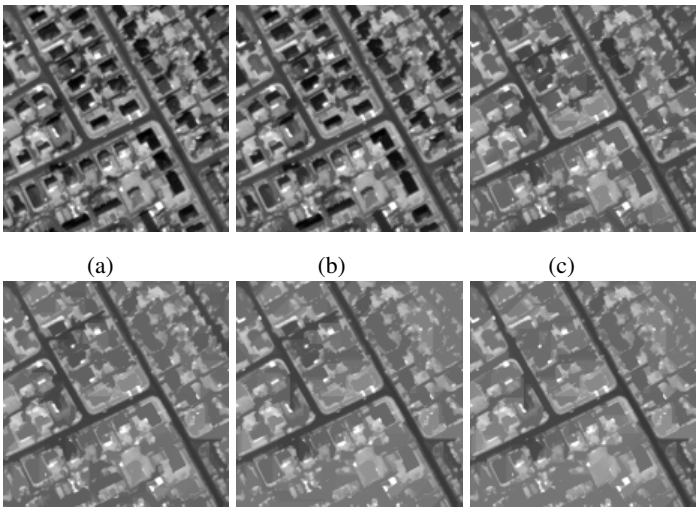
$$MP_p(i) = \begin{cases} Path\ Opening(I(p))_{-iLmin}, & \text{i=-k,...,-1} \\ I(p), & \text{i=0} \\ Path\ Closing(I(p))_{iLmin}, & \text{i=1,...,k} \end{cases} \tag{1}$$

Looking at equation 1, we notice that for a given pixel *p=(x,y)*, the Morphological Profile contains the values of p obtained by the Path Openings and Closings with increasing L_{min}. Thanks to this filters series, bright (resp. dark) linear and oriented structures not fulfilling L_{min} are removed by Path Openings (resp. Closings) during the construction of the Morphological Profile. Hence, information contained in the $MP_p(i)$ of p can be related to the length of the path which passes through p.

Using this information, we aim at determining when a pixel suffers an important change in its $MP_p(i)$ for a particular L_{min} length. Regarding road detection, the knowledge of this particular L_{min} is the key to ascertain if a pixel belongs to a road or not. This two-class classification is possible because pixels belonging to roads present medium to high L_{min} values, whereas non-road pixels present lower ones.

Fig. 7 illustrates an example of Morphological Profile construction. Fig. 7(a) shows the original image from IKONONS satellite with 1m resolution whereas Fig. 7(b)(c)(d)(e)(f) are different filtered results of path closings with increasing values of L_{min}. Note that elements not forming paths increase their gray level in each iteration. For instance, the dark squares buildings present in Fig. 7(a)(b) increase their gray level disapearing for L_{min} upper than 10. As L_{min} increases , it is possible to observe how more and more features are removed but the road network remains unaltered.

On the other hand, it should be noticed how roads not fulfilling L_{min} are also removed from the image. For example, the road appearing in the top right corner in Fig. 7(d) is removed at the next step (Fig. 7(e)). Based on this observation, the length of the actual paths contained in the VHR image can be estimated.



(a) (b) (c)

(d) (e) (f)

Figure 7: Morphological Profile construction. (a) Original Image; (b) Path Closing L_{min}=10; (c) Path Closing L_{min}=30; (d) Path Closing L_{min}=60; (e) Path Closing L_{min}=90; (f) Path Closing L_{min}= 120

In order to identify the characteristic size of an object, the usual procedure consists in computing the derivative of the Morphological Profiles [2] [3]. This approach fails in our case. As a matter of fact, it assumes that all the pixels belonging to one road are removed by the same length L_{min}. This limitation occurs because of the complexity of VHR remote sensing images, where pixels belonging to the same road appear as disconnected sets with different gray level values. Therefore, we introduce a new approach to interpret the obtained Morphological Profiles in order to determine when pixels belonging to one road are removed by the operator with a given L_{min} value.

3. Extraction of linear geometrical information

3.1. Morphological Profiles Analysis

The proposed road map detection is based on the property that pixels belonging to roads present Morphological Profiles with similar characteristics. For example, in the case of bright (resp. dark) road-pixels, corresponding Morphological profiles contain a set of values representing a decreasing (resp. increasing) curve. In the following, for the sake of clarity we focus on the detection of dark road segments. The detection of brigth ones is achieved by using dual operators. An example of corresponding Morphological Profile is shown in Fig. 8.

In Fig. 8, the horizontal axis represents the L_{min} values used at each Path Opening or Closing iteration. The vertical axis features the evolution of the Gray Level Value of the pixel.

It can be observed how the application of Path Closings isolates this dark pixel in a gradual way, progressively increasing its gray level value as L_{min} increases. Because of this gradual increase, it is difficult to determine a big slope change which would allow considering that the road containing this pixel is completly removed. Consequently, we propose to determine this specific moment using the large flat zone found after the strong slope.

We assume that the break of the slope is reached when L_{min} corresponds to the length of the road. Thus, a road length estimation can be performed assigning to each pixel the value L_{min} corresponding to this point.

In practice, the large flat zone appears in the road pixels Morphological Profiles around the same gray level. Consequently, it is possible to define a typical gray level *MGL* corresponding to the break of the slope. The estimation of this value is detailed in the next section.

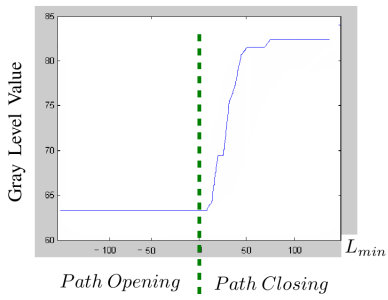


Figure 8: Example of Morphological Profile for a pixel belonging to a dark road segment

3.2. Median Gray Level Estimation

MGL is defined as the typical gray level that road-pixels possess on the original image. In order to estimate it, we construct a binary mask *M(x,y)* mostly containing typical road-pixels. It is constructed as Fig. 9 shows:

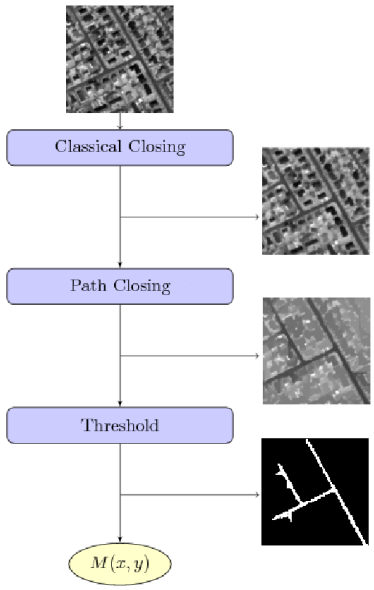


Figure 9: Flowchart describing *M(x,y)* construction

1. A standard morphological closing is applied in order to isolate all the features darker than their surrounding.
2. A Path Closing removes all the remaining features that are not road-shaped. We must choose a L_{min} large enough to allow detecting the longest linear structures in the image (roads).
3. All the pixels with a low valuew are retained for the mask. This very premissive decision ensures an optimal detection probability.

The median gray level value *MGL* is then computed as the median value of the pixels contained in the application of *M(x,y)* on the original image.

3.3. Road detection

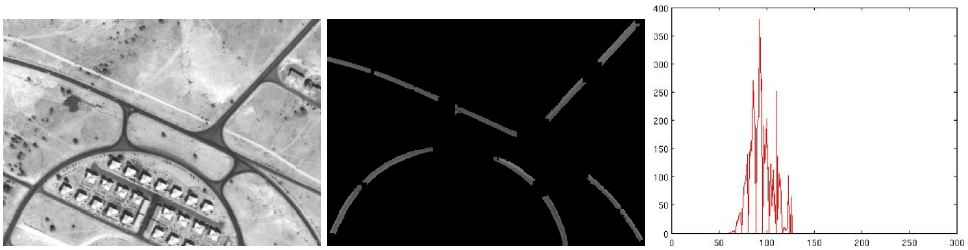
As previously mentioned, our aim consists in studying $MP_p(i)$ in order to estimate the length of the path which passes through each pixel p. Using the *Median Gray Level* definition, this estimation is performed by $L'(p)$ defined as:

$$L'(p) = min\{L_{min} \mid MP_p(i) > MGL\} \quad (2)$$

At this point, a road map can be easily performed selecting all the pixels having a value $L'(p)$ larger than a given threshold. Knowing that $L'(p)$ values are larger for the pixels contained in roads.

4. Experiments

In order to evaluate the proposed method, three experiments are presented to extract roads from IKONOS and QuickBird images. In the first experiment, the Quickbird image shown in Fig. 10(a) is used. It contains 420 x 300 pixels where some dark roads are featured.

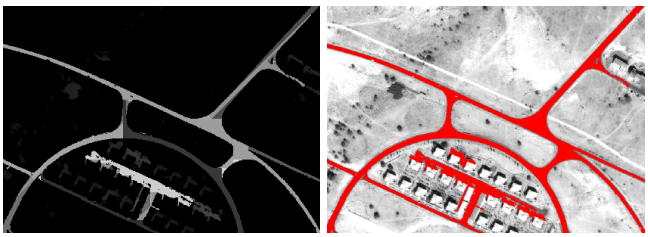


(a) (b) (c)

Figure 10: (a)Exemple of VHR image; (b) Mask Application; (c) Histogram.

As previously explained, a binary mask *M(x,y)* is extracted and a typical *MGL* value is computed. The procedure described in section 3.2 is used.
Once *M(x,y)* is defined, its application on the original image is performed. The result of this application is shown in Fig. 10(b) where the majority of the detected pixels indeed belong to the road network.
As an illustration, the histogram of Fig. 10(b) is constructed in order to extract the median gray level value of detected pixels. The obtained histogram can be observed in Fig. 10(c).
The computed median value in the histogram is 115. It is taken as the typical gray level value of road pixels in the original image.

After setting *MGL* to 115, we assign the corresponding $L'(p)$ length estimation to each pixel, as defined by Eq. 2. The resulting image is presented in Fig. 11(a). Pixels belonging to roads present higher values than non-road pixels. Finally, a road map can be extracted from Fig. 11(a) setting a simple threshold *T*. In order to minimize the non detection rate, *T* is chosen according to possible roads lengths. In the case of Quickbird data, with a 0.7m spatial resolution, we assume that a road is at least 50 m long, hence we set *T=50* .
Thus, the road map is constructed by selecting all pixels exhibiting values larger than *T*. The obtained road map is illustrated in red in Fig. 11(b).



(a) (b)

Figure 11: Road Extraction Results. (a) $L(p)'$ Estimation; (b) Road Map Result

The obtained results show how roads positions have globally been extracted with a good precision and a good reliability. Furthermore, only a few false alarms remain. The extracted road map of Fig. 11(b) can be compared with

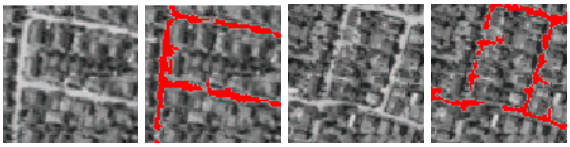
past results [13] improving the accuracy of the results.

In order to assess the genericity and the robustness of the method, a second experimental study is presented. The proposed algorithm has been applied to Fig. 12(a) (image acquired by the satellite IKONOS). This image contains some different types of roads at various orientations with a few obstacles (vehicles, buildings, markers). It should be noticed that in this second data test, roads appear as bright features. Consequently, the very same detection procedure is applied, but using dual operators (openings instead of closings, leading to a decreasing Morphological Profile instead of an increasing one).

(a) (b)

Figure 12: Second Test Results. (a) VHR IKONOS Example containing 300x300 pixels; (b) Road Map Result

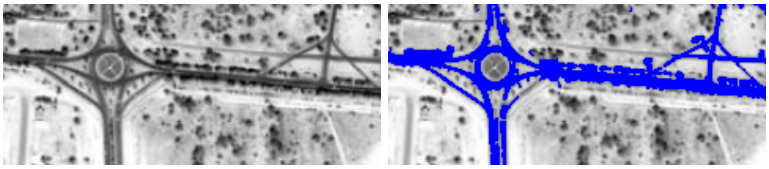
The obtained result is presented in Fig. 12(b), with very good detection performances, including elongated but not necessarily perfectly straight roads. The occlusion of roads by trees or shadows explains disconnected segments. Fig. 13 features such cases where the method fails. However, one should underline that any method working at the pixel level would fail in the same way. In such cases, the road actually disappears under trees or in the shadow. In order to cope with these situations, a high level of representation is needed. This is usually addresses using some post processing such as graph reconnection [18].



(a) (b) (c) (d)

Figure 13: Example of imperfections.(a)(c) Original Images;(b)(d) Road Extraction Results

Finally, the third experiment is carried out on the IKONOS image shown in Fig 14(a). This image has been proposed since a difficult traffic circle is featured. The result of applying our method can be observed in Fig. 14(b). As can be seen, major parts of the road networks have been extracted. However, a problem of accuracy is clearly found for this image. The problem is linked to the dark trees situate besides the roads. Being connected and aligned, they are interpreted as roads. This fact occurs because these non-road dark pixels touch directly roads pixels.



(a) (b)

Figure 14: Third Test Results. (a) VHR IKONOS Second Example; (b) Road Map Result

5. Conclusions

In this research, an automatic road extraction methodology has been presented using high-resolution aerial imagery. The proposed technique is based on the assumption that roads are linear connected paths. Then, roads have been detected thanks to a granulometric-like analysis using Path Openings and Path Closings.
In our approach, these path operators have been proposed since they are useful for the analysis of thin, elongated but not necessarily perfectly straight structures. Therefore, dealing directly with rectilinear or curved road segments, these morphological filters have demostrated their effectiveness.
The granulometric-like analysis is performed constructing for each pixel its Morphological Profiles. The intuitive idea of morphological profile can theoretically be interpreted as a variation of notion of morphological spectrum. In the proposed method, morphological profiles are used to analyze object size and shape features to determine candidate roads in each level.
The similarity between the morphological profiles of pixels belonging to the roads of one given picture has allowed to develop a new road detection technique. At this point, the definition of Median Gray Level value is presented to achieve the automatization approach.The obtention of this value has also been presented in some different steps.
Experimental results have showed that it is possible to extract the road network accurately in terms of completeness and correctness. However, a few road segments remain disconnected in the final results. Most of them correspond to areas where the roads are hidden by trees or by shadows. The next step would be to apply a classical post-processing aiming at constructing a fully connected graph using higher level representations [18]. Also, a pre-processing task to solve the problem regarding the small non-road features touching roads pixels should be studied.

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