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Hierarchical Classification-based Radon road extraction (HCBRRE) : A Radon based Collaborative Approach For Road Extraction

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Acceptance Letter

July 2, 2012

Mr. Aymen SELLAOUTI
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Dear Mr. Aymen SELLAOUTI

Paper ID:	**P0319**
Paper Title:	**Hierarchical Classification-based Radon Road Extraction (HCBRRE)**
Authors:	**Aymen SELLAOUTI, Hmida ROJBANI, Atef HAMOUDA, *Cedric WEMMERT, *Aline DERUYVER**
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The review process for the 12th International Conference on Control, Automation, Robotics and Vision (ICARCV 2012) has been completed. All the papers submitted to the conference from 44 countries were peer reviewed by international experts.

Based on the recommendations of the reviewers and the International Program Committee, I am pleased to inform you that your paper identified above has been accepted for presentation in ICARCV 2012. You are cordially invited to present the paper at ICARCV 2012 to be held on December 5-7, 2012 in Guangzhou, China.

The acceptance of your paper is made with the understanding that the camera-ready paper will be uploaded to the ICARCV 2012 website by September 1, 2012 and at least one author must register and attend the conference to present the paper.

This invitation is **not** an offer of any financial supports whatsoever for conference registration OR travel expenses to/from the conference OR any other forms of subsistence allowances while in Guangzhou, China. This letter is issued on the expectation that you will register for the conference and pay by the stipulated due date the required registration fees as notified on the web site.

We look forward to welcome you at ICARCV 2012 in Guangzhou, China.

Yours sincerely,

Chien Chern CHEAH
Program Chair, ICARCV 2012

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Hierarchical Classification-based Radon road extraction (HCBRRE)

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***Abstract*—A hierarchical classification based road extraction approach is proposed in this paper. In order to extract road network, a spectral based-classification associates a confidence score to each region in the image. This score is used to extract road region and its constraints for each iteration of the hierarchy. Road localization is based on Radon transform and expert knowledge. The quality assessments in urban area images show the benefits of the introduced approach.**

***Index Terms*—Collaboration, Road extraction, Radon transform.**

I. Introduction

Due to the availability of remotely sensed images and advances in computing technologies, many methods have been developed in order to extract cartographic items. In this context, we have been interested in extracting roads networks from satellite images. Research on road extraction from satellite images can be traced back to the 70's. Early approaches for road detection were developed using both low and high-resolution aerial photographs [1]. Roads are among the most important objects that are extracted from high resolution images; they are necessary for many applications, for example navigation systems or spatial planning. Many interesting works have been devoted to road extraction. Among these, we could cite the adaptive template matching [2], snakes model [3], perceptual grouping [4], multi-scale or multi-resolution approach [5] and GIS data guided [6]. The concept for road network extraction is relatively simple, but reliable processes remain a difficult challenge. There exists no generic algorithm sufficiently reliable for all practical use. Road extraction remains largely, at least in typical production environments, costly manual process. The major drawback of low-level techniques is their sensitivity to Noise, particularly for high resolution images in which artifacts inherent to the observed scene is added (for example, tree shadows on the roads). To reduce this sensitivity to noise, some authors propose to combine different operators [7]. Present main approaches are those like texture analysis applied to a single layer, Point processes [8] and multicriteria directional operator [9]. All these models or algorithms are mainly based on radiometric characteristics and geometric constraints of road information in the imagery thus do not exploit fully the spectral information of roads. So that, the road extraction methods still have problems in popularization and application, the extraction accuracy cannot satisfy the needs of engineering application, the automation is in a relatively low level and the performance is limited by either road materials or complex road networks. However, in the last decade, there have been frequently use of the classification-based approach for road extraction and specially in the multispectral images (MSI) [10] where they proved a good extraction results. The Classification-based approach are composed of two steps; (*i*) a bi-classification (BC) of the image in two classes which are road and non road. This classification is generally a spectral-based classification. The problem of this BC is that it doesn't allow the introduction of adjacency constraints in the followed step ; (*ii*) the second step is object localization using the object classified in the first step to extract the road network. In this work, we introduce a new approach for network road extraction based on a supervised object-based classification which provide clues on the membership of objects while assessing the confidence we have on this information and a localization phase based on Radon transform (RT). It only focuses on road localization and does not discuss a tracking step. This paper is outlined as follows: after introducing the proposed approach in section 2, we present the two major step of this approach and the integration of spatial knowledge step. Experiments and extraction results are given in section 3. Finally we summarize our research and conclude the paper in section 4.

II. The HCBRRE approach

We propose a Hierarchical Classification-based Radon road extraction (HCBRRE) approach. This approach is split into two steps, as depicted by Figure 1:

- A first preprocessing step which is a data preparation for the next step. This allows the decomposition of the image into a set of homogeneous objects based on low-level features such as radiometry. After the extraction of

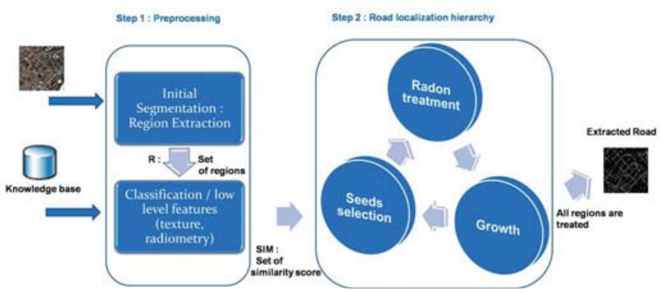


Fig. 1. Workflow of the proposed approach

homogeneous objects, we classify the image by calculating a score for each region based on low-level features provided by the expert. This score will introduce the notion of confidence that provides a degree of validity of the labeling of each object and allows the creation of a growth hierarchy.

- The second step is the hierarchical localization step which is an iterative step composed of three phases for each iteration ; (*i*) the selection of the set of the most confident region including the road segments. This set represents objects not yet processed and that maximize the similarity score ; (*ii*) for each road object in this set, we select the nearest neighbors and we apply a RT on it to find the road direction ; (*iii*) the localization phase is guided by the Radon given direction and the road expert knowledge.

A. Preprocessing

1) Segmentation: The choice of the segmentation algorithm is not very important in this approach as long as it fulfills the criterion of over-segmentation. Indeed, given the properties of region growing algorithms, which are based on the fusion of fragments of an object to be detected, it is clear that a sub-segmentation of the image implies a loss of some objects. We have chosen the watershed algorithm that easily allows an over-segmentation of the image.

2) Classification: We propose a classification based on a confidence score. This classification allows assessing the regions built during the initial segmentation and the possible classes of the image. This score will assess the validity of the regions based on the knowledge provided by the expert. We use the similarity score proposed by Forestier et al.[11], [12]. This score is based on an attribute-oriented approach as it uses low-level knowledge of the image that are formalized in the form of low-level descriptors. In [12], authors use the similarity score to propose an object recognition method based on an ontology built by experts. The regions of the segmentation are characterized by features related to spectral, spatial and contextual properties and classified through a matching process between an object and the concepts of the ontology.

The proposed similarity score is used to check the validity of the attribute values of a region with respect to the intervals defined by the expert. The expert provides an interval representing the minimum and maximum value that can take each attribute for each class. The similarity score compares the attributes values of a region with the attributes of the object to classify.

Note 1: **(region)**: Let R be the set of regions obtained from segmentation. $R = \{r_i\}_{i\in[1,N_R]}$ where N_R represents the cardinality of R.

Note 2: **(class)**: Let C be the set of classes in the image. $C = \{c_j\}_{j\in[1,N_C]}$ where N_C denotes the cardinality of C.

Note 3: **(attribute)**: Let A be the set of features identifying a class. $A = \{a_k\}_{k\in[1,N_k]}$ where N_k is the cardinality of A.

Definition 1: **(Validity degree)**: Let $Valid(a, c_j, r_i)$ the degree of validity between a class c_i and a region r_i for a given attribute a_k and let $v(r_i, a_k)$ be the value of the attribute a_k for the region r_i.

$$Valid(a, c_j r_i) \begin{cases} 1 \;; \quad v(r_i, a_k) \in [min(c_j, a_k), max(c_j, a_k)] \\ \frac{v(r_i,a_k)}{min(c_j,a_k)} \;; \qquad v(r_i, a_k) < min(c_j, a_k) \\ \frac{max(c_j,a_k)}{v(r_i,a_k)} \;; \qquad v(r_i, a_k) > max(c_j, a_k) \end{cases} \tag{1}$$

Definition 2: **(Similarity score)**: The similarity score $Sim(r_i, c_j)$ is computed according to the validity between the region r_i and the class c_j of each attribute weighted by a weight $w(k, c_j)$:

$$Sim(r_i, c_j) = \frac{\sum_{a\in A} w(a_k, c_j) Valid(a_k, c_j, r_i)}{\sum_{a\in A} w(a_k, c_j)} \tag{2}$$

Definition 3: **(Set of similarity)**: We define the set of similarity as all the similarity scores of any region $r_i \in R$ with respect to any class $c_j \in C$.

$$SIM = \{Sim(r_i, c_j) | r_i \in R \; et \; c_j \in C\} \tag{3}$$

B. Growth and extraction hierarchy

This step is an iterative process. Based on the sets of regions R, the set of classes C and the set of similarity scores SIM, it allows the creation of the growth hierarchy based on the confidence we have for each region. Moreover, roads have specific properties that differentiate them from other classes. Indeed, they present in an optical image a more homogeneous radiometry than buildings. They are usually paved with asphalt, have linear and parallel edges, a width between 6 and 25 m and are usually at ground level, and do not shade. Most roads do not contain vegetation [13]. Based on these properties and the confident road objects extracted in each iteration, we propose a hierarchical localization roads approach using RT.

The creation of the hierarchy is preceded by a calculation based on the similarity scores as we explain in the follows [14].

Definition 4: For a region $r_i \in R$, we define the set of classes that maximize the similarity score $(Sim(r_i, c))$ among all the classes $c \in C$. We note $\delta(r_i)$ this set:

$$\delta(r_i) = \arg\max_{c\in C} Sim(r_i, c) \tag{4}$$

Definition 5: For each region $r_i \in R$, we define $S_{max}(r_i)$ and $C_{max}(r_i)$ as follows :

$$C_{max}(r_i) = \begin{cases} random(\delta(r_i)) & if\ |\delta(r_i)| > 1 \\ \delta(r_i) & otherwise \end{cases} \quad (5)$$

$$S_{max}(r_i) = \begin{cases} Sim(r_i, C_{max}(r_i)) & if\ |\delta(r_i)| > 1 \\ 0 & otherwise \end{cases} \quad (6)$$

($S_{max}(r_i)$) represents the maximum similarity score of the region r_i for all classes of C. In the case where $\delta(r_i)$ has more than one class, we deduce that there is a confusion *(i.e. this region is no longer a trustworthy region but a conflictual region)*. In this case, $C_{max}(r_i)$ will arbitrarily take one of the classes of $\delta(r_i)$ and $S_{max}(r_i)$ will be assigned 0. If $\delta(r_i)$ contains a single value, then it will be assigned to $C_{max}(r_i)$ and $S_{max}(r_i)$ will be the similarity score $Sim(r_i, C_{max}(r_i))$ of the class C_{max} for the region r_i.

The calculation of C_{max} and S_{max} will serve as basis for the iterative algorithm of hierarchical growth. Each iteration of this algorithm is equivalent to a growth level of the hierarchy, and is composed of three steps:

- seeds' extraction
- classification challenging based on spatial constraints.
- growth.

We denote by $candidates_{k-1}$ all the candidate regions for the extraction of seeds at iteration $k(k >= 1)$, and $Seeds_k$ all seeds extracted during this iteration. The set of initial candidates ($candidates_0$) is initialized to all regions R composing the image: $candidates_0 = R$.

1) Seeds' selection: The extraction of all seeds of level k from the set $candidates_{k-1}$ of the regions not yet been processed in previous levels of the hierarchy. The seeds extracted at this level are the regions r_i that maximize $S_{max}(r_i)$ among all candidate regions at this level, *i.e.*,

$$Seeds_k = \arg\max_{r \in candidates_{k-1}} S_{max}(r). \quad (7)$$

Also, we decompose $Seeds_k$ into two sets:

- $Sroad_k$ that contain the seeds of class road.

$$Sroad_k = \{r \in Seeds_k | C_{max}(r) = road\}. \quad (8)$$

- $Sconstraint_k$ that contain the seeds of other classes.

$$Sconstraint_k = \{Seed_k \setminus Sroad_k\}(r). \quad (9)$$

2) Radon seeking direction treatment: To define the area of growth for each seed of level k, we apply RT to detect the growth direction and we use the expert knowledge on the roads to limit the width of this growth.

Starting from the confident road seeds extracted from the selection seeds phase and the set of extracted road segments (this set is empty in the first iteration and will contain the extracted road segments resulting of each iteration), and taking in consideration that the mainly road form is rectangular, even the more complex form can be seen as piecewise linear forms, we choose the RT to detect the road direction for each seed. RT is a widely known tool to precisely identify linear forms in an image and is mainly used for road network extraction [15],[10]. Indeed, experiments have shown that the RT-based linear feature detector is a good choice because of its robustness to noisy pixels (*i.e. misclassified pixels*), its positional accuracy, and its capability to estimate line width. In our approach, we propose a new vision of RT. In fact, Rt is used as a direction detector. We remind that for an image $f(x, y)$ defined on a two-dimensional Euclidean space, its continuous RT is then defined as [16]:

$$T_R f(\rho, \theta) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x, y)\delta(\rho - x\cos\theta - y\sin\theta)\mathrm{d}x\mathrm{d}y. \quad (10)$$

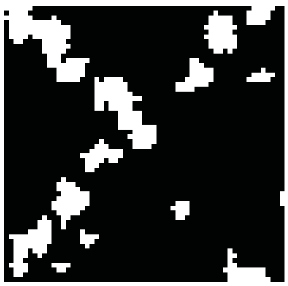
Where $\delta(.)$ is the Dirac function, $\theta \in [0, \pi]$ and $\rho \in]-\infty, +\infty[$. The space (ρ, θ) is usually referred to as the **Radon Space** (RS) or parameter space. The equation $\rho = xcos\theta + ysin\theta$ is the parametric equation of a straight line in polar coordinates, and the meaning of Eq.10 is to perform integration of the image along each of these straight lines, storing the integral value in the corresponding RS point. The RT has several major properties, the most important one is:

property 1 : *An image which is non zero in a single point of coordinates $(x0, y0)$ has a RT which is non zero along a sinusoidal curve of the RS, whose equation is given by $\rho = x_0 cos\theta + y_0 sin\theta$. This means that the contribution of a small filled pattern of the image (such as a small circle, square or spot), of known location, is distributed along a curve of the RS, whose analytical equation is known.*

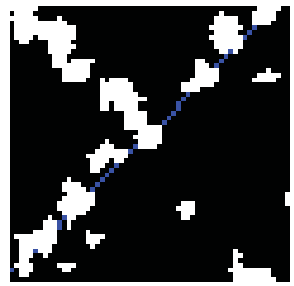
We use this property to seek for the right direction of the road in the image. For each seed in the $Sroad_k$, we take a $x \times x$ window, where the treated seed is the center of this window, which contain only the trusted road seeds (*i.e. the $Sroads_k$ of the k iteration and the road object already extracted*), the chose of the x affects the robustness of our approach in the direction road change (i.e. curves). After that we apply the RT on this window, as result we find a 180 projects and that according to the 180 angles projections used by Radon. From those projections we select the one that have the highest peak. This peak means that in this angle projection most of the road segments in the treated window are in the same direction. Indeed, the radon will accumulate those pieces of road in every angle of projection, and it will calculate the Radon sum of every projection. The highest sum, (i.e. highest peak in the RS), means that the most participant segment in the Radon calculation are in the same direction.

In figure 3, we give an illustration of the calculation of the direction shown in the figure 2. The figure 3(a) is the Radon space of the image fig.2(a), the lightest points represent the peaks. The fig.3(b) is the highest peak which gives the direction in blue in the figure 2(b), the fig.3(c) is the second highest peak which is the direction opposite of the first one, but because the missing part in that direction, then this peak came the second. And the last one fig.3(d) is a projection where the accumulation of the segment part do not give a single direction, instead there are multiple peaks be distributed for each set of segments. For every segment in $Sroad_k$ set, we will have the same treatment with the RT.

In the next phase, the road growth must be limited in a

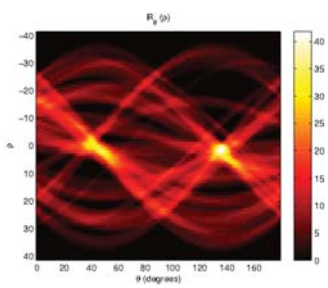


(a) Input image.

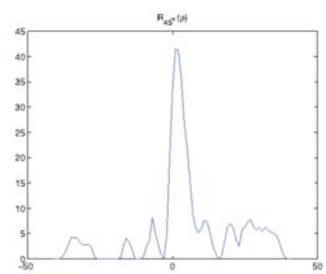


(b) The direction given by the RT treatment.

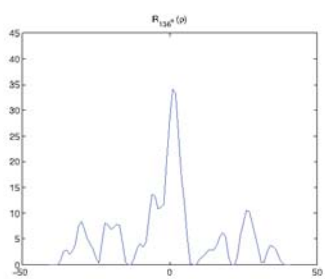
Fig. 2. An example of the direction on a test image.



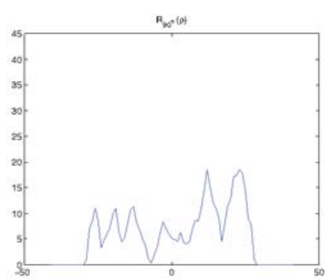
(a) the Radon Transform of the input image(2(a))



(b) the projection according to angle $45°$ (the highest peak)



(c) the projection according to angle $136°$



(d) the projection according to angle $90°$

Fig. 3. The Radon space of the fig.2(a) and some of its projection

specific zone based on road characteristic. The first one is the growth direction (i.e. the road direction in the image), each of the segment in the $Sroad_k$ will have a growth zone according to the direction given by the previous treatment. The second characteristic of the growth zone is the size. The width of the zone is average width of the road in the image, we take this information from the expert knowledge that we extract from the FoDoMust [12] dictionary, that represent a set of high and low level expert knowledge like area, perimeter, high, width, etc. Moreover, the high part of the zone is depends on the size of the RT window.

3) Road growing: The region growing begin from each seeds of level k. This growth is based on a growing algorithm that allows merging each seed with its neighboring regions based on a set of homogeneity criteria. This fusion is limited in the growing zone defined by the previous treatment and it is constrained by a set of expert road knowledge and a set of rules specific to the hierarchy and manages the integration of constraints and growth within the hierarchy. Indeed, a seed of level k cannot change the state of a seed of lower level.

Definition 6: $(fusion\_road_k)$ is defined by all the regions that have been merged in the level k with one of the seeds of $Sroad_k$.

$$fusion\_road_k = \{r \in candidates_{k-1} | r \text{ } has\ been\ merged\ in\ the\ level\ k\}. \quad (11)$$

All candidates regions in the level $k+1$, denoted $candidates_k$, will be the set of candidates of the level k after the removal of parts merged regions and $Sroad$ and $Sconstraint$ of the level k.

$$candidates_k = candidates_{k-1} \setminus \{fusion\_road_k \cup Sroad_k \cup Sconstraint_k\}. \quad (12)$$

Then from this set, we reiterate in the same manner until exhaustion of all the candidates. The pseudo-code of algorithm of the growth is given by algorithm 1:

Algorithm 1: Growth algorithm

Input: R the set of regions of the image obtained by segmentation, SIM the set of similarity scores for the regions of the image.

Output: candidates the set of candidates to be seed, Seed the set of seeds and fusion the set of regions merged for each level of the hierarchy.

Begin
  $candidates_0 = R,\ k = 1,\ Sconstraint = \emptyset$;
  while $candidates_{k-1} \neq \emptyset$ **do**
    $Seed_k = \arg\max_{r \in candidates_{k-1}} S_{max}(r)$
    $Sroad_k = \{r \in Seed_k | Cmax(r) = road\}$
    $Sconstraint_k = \{Seed_k \setminus Sroad_k\}$
    $Sconstraint = \{Sconstraint \cup Sconstraint_k\}$
    $fusion\_road_k = \{r \in candidates_{k-1} \setminus Seed_k | r\ merged\ in\ level\ k\}$
    $candidates_k = \{candidates_{k-1} \setminus fusion\_road_k \cup Seed_k\}$
    $k = k + 1$;
  endw
End

C. Integration of spatial knowledge

In the majority of classification based road extraction approaches, the problem comes down to a binary classification (road and not road). However, this classification never integrates spatial or neighborhood knowledge. In our approach, we propose to detect all classes in the image, to be able to use adjacency information in the process. Indeed, spatial knowledge can be expressed as adjacency information between the different classes. In each level of the hierarchy, and before starting the growth phase, the seeds will inject adjacency constraints on their respective neighborhoods. The

Algorithm 2: Integration of spatial knowledge

Input: $Seed_k$,SIM and $candidates_{k-1}$.
Output: $Seed_k$,SIM and $candidates_{k-1}$.

Begin
  forall the $r_i \in Seed_k$ **do**
    $set = (neighbors(r_i) \cup candidates_{k-1})$
    if $S_{max}(\arg\max_{r \in set} S_{max}(r)) < S_{max}(r_i)$ **then**
      //If r_i have the maximal confidence compared with his neighbors
      forall the $r_j \in neighbors(r_i)$ **do**
        while $C_{max}(r_j) \in SC(C_{max}(r_i))$ **do**
          $Sim(r_j, C_{max}(r_j)) = 0$
        endw
      endfall
    else
      $Flag = 0$ //to verify if r_i is a region of conflict
      forall the $r_j \in neighbors(r_i)$ **do**
        if $C_{max}(r_j) \in SC(C_{max}(r_i))$ **then**
          $Sim(r_j, C_{max}(r_j)) = 0$
          $Seed_k = \{Seed_k \backslash (r_j)\}$
          $candidates_{k-1} = candidates_{k-1} \cup (r_j)$
          if $S_{max}(r_i) = S_{max}(r_j)$ **then**
            $Flag = 1$
          endif
        endif
      endfall
      if *Flag==1* **then**
        $Sim(r_i, C_{max}(r_i)) = 0$
        $Seed_k = Seed_k \backslash (r_i)$
        $candidates_{k-1} = candidates_{k-1} \cup (r_i)$
      endif
    endif
  endfall
End

initial classification will be re-evaluated in cases of conflict. In the case where two seeds of the same hierarchy have an ambiguity due to the constraints of adjacency, then there is confusion and these seeds lose their confidence and become conflict regions. They will lose their places in the hierarchy and the similarity score of these classes will be given to zero and will be reassigned in the set of candidate regions. So, we will have $Sim(r_j, C_{max(r_j)}) = 0$ and $Sim(r_i, C_{max}(r_i)) = 0$. Otherwise, we keep the class that maximizes the similarity score and which validates the adjacency constraint.

Definition 7: **(Neighbors)**: Let neighbors(r_i) the set of regions r_j that are adjacent to r_i.

$$neighbors(r_i) = \{r_j \in R | r_i \text{ and } r_j \text{ are adjacent}\} \quad (13)$$

Definition 8: **(Spatial constraints)**: Let $SC(c_i)$ the set of classes c_j that represent the spatial constraints of the class c_i.

$$SC(ci) = \{c_j \in C | c_i \text{ and } c_j \text{ can not be neighbors}\} \quad (14)$$

Algorithm 2 illustrates the integration of spatial constraints in the hierarchy.

III. Experiments

We tested our approach on a Quickbird image covering urban areas of Strasbourg, taken in 2008, having four bands, each band with a resolution of 2.44m/px. To illustrate our experiments, we test it on a set of test area. We present two examples of test area. Figure 4(a) presents a spars area and the figure 5 the result of road localization. Figure 5(a) presents a dense area and the figure 5(b) the result of road localization. We remarque that the majority of the road are localized in the two area but the result of sparse image is better than the dense one. We also notice false alarm objects in the two image and this is due to the noise. Road completeness and correctness [17] are used to assess the accuracy of the road extraction. The completeness is the ratio of correctly extracted road segments to the total road segments from the reference image. The highest value is 1. The correctness is the ratio of correctly extracted road segments to the total segments of the extracted road network. The optimal value is also 1. The results of extraction are compared with manually digitized reference data to conduct an accuracy assessment. In table I we present the ratio of the different types of the extracted segments in each test area. where NCI stands for the number of the segments correctly identified as road, NL is the exact number of road segments in the image and FA represents the number of false alerts (number of non-road segments identified as road by the system).

TABLE I
ROAD EXTRACTED RESULTS

	site1(figure.4(a))	site2(figure.5(a))	site3	site4	site5
NCI	90	88	103	30	82
NL	106	98	111	34	98
FA	19	12	13	2	12

(a) Input image. (b) The extraction results

Fig. 4. The Extraction results of the first test area.

To compare our results, we select two methods from the literature; we take consideration the fact that those two methods are using the same type of images as ours (i.e. Quickbird MSI). The selected approaches are Zhang et al. [18] in 2010 and Zhang and Couloigner [19] in 2006.

(a) Input image. (b) The extraction results

Fig. 5. The Extraction results of the second test area.

Zhang and Couloigner [19], chose a simple k-means clustering algorithm for image segmentation and used fuzzy logic classifier to identify road cluster. They develop an iterative and localized Radon transform to extract road centerlines from classified remotely sensed imagery. But, when an image contains multiple road lengths, the Radon transform detects long road components and ignores the shorter road segments. To solve this problem, Zhang and Couloigner developed and tested three approaches to partition input images in order to localize the RT. Based on their test results, they found that the gliding-box approach had the best overall performance. An iterative RT is applied locally to each road component image. At each iteration, road centerline segments are detected based on an accurate estimation of the line parameters, including line widths. In [18], Zhang et al. define an approach on the urban road extraction from high-resolution remote sensing images from the perspective of semantic network model. First, they analyze spatial features and contextual information of road. By using the method of regional segmentation edge detection, area filter and Hough transform methods respectively, they obtain the candidate nodes for the semantic network model of road.

In table II, we put a comparison between the average of the results given by our approach and the other two. The results shown in table 2 prove that our approach has approve the extraction results. In term of correctness, our approach has the best result 0.88. In term of completeness our approach is very close to the best result given by [18], this is due to the enhancement and correction applied before using the image, which leads to a better results, counter to this work, we operate directly on the pure image without any pretreatment.

TABLE II
QUANTITATIVE COMPARISON RESULTS

Methods	Completeness	Correctness
Zhang et al. [18]	**0.79**	0.81
Zhang and Couloigner [19]	0.50	0.51
HCBRRE	0.78	**0.88**

IV. CONCLUSION

In this paper, we have proposed a new hierarchical approach for road localization using RT. The approach is based on a first classification which allows object ordering based on a confidant score and to associate a semantic meaning to regions of a segmented image before the growing process based on road expert Knowledge. RT have been used to detect a road direction for each road seed segment. The results of the system are very encouraging. Moreover, we think that it is very useful to add a tracking step which can allow to extract the objects not detected and to eliminate the false alarm.

REFERENCES

[1] L. Quam, "An road tracking and anomaly detection in aerial imagery," in *Proceedings of DARPA Image Understanding Workshop*, 1978, pp. 51–55.

[2] X. Hu, "Automatic extraction of linear objects and houses from aerial and remote sensing imagery," Ph.D. dissertation, Wuhan University, China, 2001.

[3] M.Rajeswari, K.S.Gurumurthy, L. Reddy, S.N.Omkar, and Senthilnath.J, "Article: Automatic road extraction based on normalized cuts and level set methods," *International Journal of Computer Applications*, vol. 18, no. 7, pp. 10–16, March 2011.

[4] X. Hu, C. V. Tao, X. Hu, and C. V. Tao, "Automatic main road extraction from high resolution satellite imagery," *IAPRS*, pp. 203–208, 2002.

[5] I. Laptev, T. Lindeberg, W. Eckstein, C. Steger, and A. Baumgartner, "Automatic extraction of roads from aerial images based on scale-space and snakes," 2000.

[6] Q. Zhang and I. Couloigner, "Automatic road change detection and gis updating from remotely-sensed image," in *Asia GIS Conference*, 2003.

[7] M. Naouai, A. Hamouda, and C. Weber, "Urban road extraction from high-resolution optical satellite images," in *Proceedings of International Conference on Image Analysis and Recognition*, 2010, pp. 420–433.

[8] C. Lacoste, X. Descombes, and J. Zerubia, "Unsupervised line network extraction in remote sensing using a polyline process," *Pattern Recognition*, vol. 43, no. 4, pp. 1631–1641, avril 2010.

[9] M. Naouai, A. Hamouda, and C. Weber, "Detection of road in a high resolution image using a multicriteria directional operator," in *Proceedings of Computer Graphics, Visualization, Computer Vision and Image*, 2009.

[10] Q. Zhang and I. Couloigner, "An integrated approach to extracting urban road networks from high resolution multi-spectral imagery," in *1st EARSeL Workshop of the SIG Urban Remote Sensing*, HumboldtUniversitt zu Berlin, 23 March 2006.

[11] G. Forestier, S. Derivaux, C. Wemmert, and P. Gançarski, "An evolutionary approach for ontology driven image interpretation," in *Proceedings of EvoWorkshops*, ser. Lecture Notes in Computer Science, vol. 4974. Springer, Boston, Massachusetts, july 2008, pp. 295–304.

[12] N. Durand, S. Derivaux, G. Forestier, C. Wemmert, P. Ganarski, O. Boussad, and A. Puissant, "Ontology-based object recognition for remote sensing image interpretation," in *IEEE International Conference on Tools with Artificial Intelligence*, vol. 1. Patras, Greece: IEEE Computer Society, october 2007, pp. 472–479.

[13] V. Poulain, "Fusion d'images optique et radar haute rsolution pour la mise jour de bases de donnes cartographiques," PhD thesis, National Polytechnic Institute of Toulouse, Toulouse, France, octobre 2010.

[14] A. Sellaouti, A. Hamouda, A. Deruyver, and C. Wemmert, "Hierarchical classification-based region growing (hcbrg): A collaborative approach for object segmentation and classification," in *Proceeding of International Conference on Image Analysis and Recognition (ICIAR)*, Jun 2012.

[15] C. Silva, J. S. Centeno, and M. Henriques, "Automatic road extraction in rural areas, based on the radon transform using digital images," *Canadian Journal of Remote Sensing*, vol. 36, no. 6, pp. 737–749, 2010.

[16] S. Deans, *The Radon Transform and Some of Its Applications*. revised edition, Krieger, Malabar, FL., 1993.

[17] C. Heipke, H. Mayer, C. Wiedemann, and O. Jamet, "Evaluation of automatic road extraction," in *International Archives of Photogrammetry and Remote Sensing*, 1997, pp. 47–56.

[18] L. Zhang, J. Zhang, D. Zhang, X. Hou, and G. Yang, "Urban road extraction from high-resolution remote sensing images based on semantic model." in *Geoinformatics'10*, 2010, pp. 1–5.

[19] Q. Zhang and I. Couloigner, "Comparing different localization approaches of the radon transform for road centerline extraction from classified satellite imagery." in *ICPR (2)'06*, 2006, pp. 138–141.