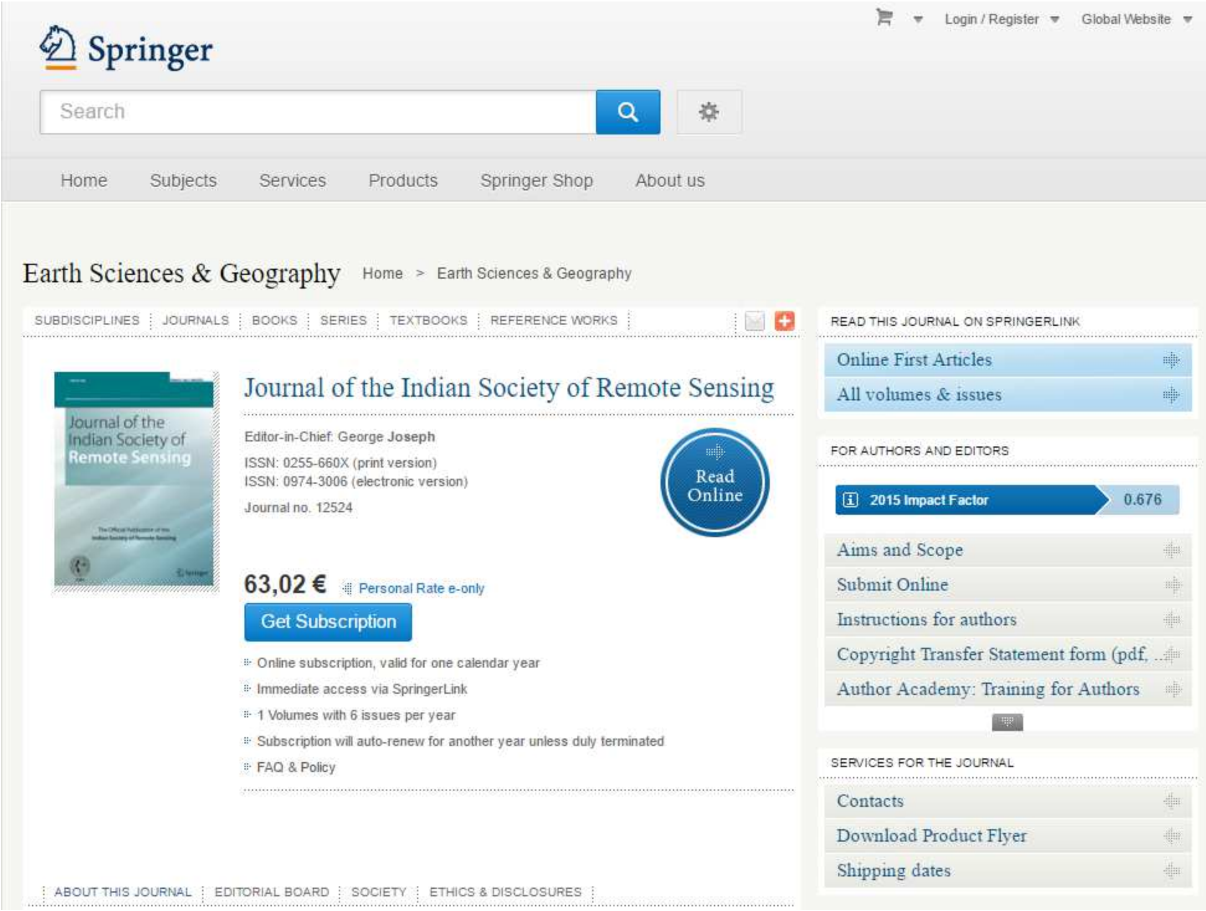

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Local Evolutionary Multi-agent System For Buildings Extraction

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Local Evolutionary Multi-Agent System For Buildings Extraction

Aymen Sellaouti · Atef Hamouda · Aline Deruyver · Cedric Wemmert · Moslem Ouled Sghaier

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Abstract Automatic building extraction remains an active research topic in the field of remote sensing. This paper introduces a new automatic approach for local evolutionary building extraction in very high resolution satellite images. The proposed method benefits of both multi-agent systems and genetic algorithms characteristics to overcome the threshold's dependency of a proposed cooperative multi-agent system between both an edge and region approach. The genetic algorithm is used to automatically find building extraction parameters for each agent based on expert knowledge. Experiments carried out on Quickbird remote sensing images of Strasbourg city (France) show the ben-

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efits of the introduced approach.

Keywords Buildings extraction · Multi-agent system · Cooperation · Local genetic algorithm

1 Introduction

So far, building extraction is still a critical feature in remote sensing. In fact, automatic building extraction remains an active research topic for many applications such as urban planning and cartography. During the past two decades, building extraction from digital images has been one of the most complex and thriving challenges faced by computer vision and photogrammetric communities. Efforts towards efficient buildings extraction processes can be categorized into three categories: edge-based approaches(Theng and Chiong, 2007; Mayunga et al., 2007; Elouedi et al., 2012), region-based approaches (Lari and Ebadi, 2007; Singh et al., 2012; Song et al., 2006) and cooperative approaches (Han et al., 2009; Lhomme et al., 2009; Laguel, 2010; Sellaouti et al., 2012b).

The main problem of region-based approaches is that boundaries of the resulted regions are usually inaccurate and do not provide a precise matching with the limits of buildings in the image. For the edge-based approaches, they can present false detections and not closed building edges. For these reasons, there has been a growing interest in the use of cooperative approaches in buildings extraction. Based on a structure promoting cooperation and local treatment, the multi-agent systems are frequently used in image processing (Laguel, 2010).

In this paper, we introduce a multi-agent region-edge cooperation method, aiming to improve the results by taking into account the complementary nature of both edge and region information. Contour detection allows to find the most evident frontiers of buildings. The region growing procedure enables to refine borders and to obtain more precise buildings. Despite the contribution of the cooperation, this approach is still threshold dependent. In fact, both thresholds used for edge detection and region growing are image dependent. Despite that, these thresholds can give better results if they depend on the building itself. Indeed, building characteristics can differ from one part to another in the same image. In this context, we use a local evolutionary approach to overcome the threshold dependency.

The aim of this paper is to present a cooperative multi-agent system for a local evolutionary buildings extraction. The second section presents related work. Then, the cooperative multi-agent system is introduced in the third section. The fourth section presents the evolutionary approach based on genetic algorithm and shows how a local approach can improve the results of our system. In the fifth section, the efficiency of our approach is demonstrated by experiments on several images. Finally, the last section gives some conclusions and draws some perspectives of this work.

2 Related Works

Many approaches for building extraction have been proposed in the literature. These approaches can be decomposed in three classes: edge-based approach, region-based approach and mixed approach.

Edge-based approaches are especially based on geometric features. Many researches were and are still using these approaches. Haverkamp (Haverkamp, 2004) uses the Nevatia-Babu filter with non-maximum suppression to extract edge information. He retrieves all chains form edges and right angles included in a database. Then hypotheses are proposed to find the missing edges. This approach is only valid for buildings with linear edges. Theng and Chiong (Theng and Chiong, 2007) find that choosing buildings' corners as a starting point can solve the problem of snakes' initialization used in buildings extraction. Mayunga et al. (Mayunga et al., 2007) use radial casting algorithm to initialize snakes contours, and the fine measurements of building outlines is carried out using snakes model. Another edge-based approach is the work of Elouedi et al. (Elouedi et al., 2012). In this work, the authors propose a generalized form for the well known Radon transform, the new transform can detect directly the rectangular form in an edge map without any post-treatment. Unfortunately, this approach failed to detect the buildings having a more complex shape like a T or a L. The main drawback of the edge-approaches are the edge themselves. How relevant is the used edge map? In fact, the extracted edges depend on the image and the edge extraction algorithm. Edge lines may be missed and objects can be fused due to low contrast, shadow overcast and occlusion effects.

The region-based approaches detect the body of buildings. Song et al. (Song et al., 2006) propose a region-based approach for building detection in high-resolution satellite image with densely build-up buildings. In the first step, the prior building model is constructed with texture and shape features from a training building set. After over-segmentation of input image into many small regions, they identify regions which have a similar pattern with prior building model. These regions are called building like regions (BLR). Then BLRs are grouped to get candidate building regions (CBR), having a similar shape as the prior building model. Then, lines having strong relationship with each CBR are extracted. From these lines and CBR boundaries, 2-D rooftop hypotheses are generated. At last, shadows and geometrical rules are used to verify the hypotheses. The limitations of this method are that the detected results are dependent on the initial over-segmentation and line detection. Singh et al. (Singh et al., 2012) use NDVI based segmentation and morphological operations. This approach uses both spatial (morphological operations) and spectral (NDVI based segmentation) properties of an image scene for building detection. After the segmentation, the authors use the morphological operation to separate the roads from building regions on the basis of their spatial properties ; in fact, roads exhibit elongated and larger area than buildings, while most buildings have rectangular rooftops. The main drawbacks of the region-based approaches, is the inaccurate edge detection and its dependency on the ability to extract meaningful homogeneous regions especially for high resolution images which are characterized by a high level of details.

This leads us to the combination of these different approaches to enhance the quality of the results. Lhomme et al.(Lhomme et al., 2009) use texture information to detect buildings. They propose to classify buildings into two parts: body and peripheral. Then, they build a voting matrix and consider maxima as centers of the buildings. Han et al. (Han et al., 2009) combine regional information with edge features, which could avoid the limitations of traditional methods. Firstly, the irrelevant regions are filtered out from large images by extracting texture features, leaving buildings distributed in the remaining urban areas. Secondly, boundaries of objects are extracted and all the edges are tracked through a chain code method. Finally, the short straight lines are linked to construct borders and extract rectangular building rooftops.

To sum up, tacking the benefits of both approaches (region and edge) and combining them gives the best extracting result. For that reason, we introduce a new way of combining the edge-based and region-based approaches which will be presented in the next section.

3 An edge-region cooperative multi-agent approach for buildings extraction

Our proposition is to design a multi-agent system for buildings extraction from high resolution satellite images. The guiding idea of this approach is to integrate both edge-based and region-based approaches. The major drawback in the initial approach is the threshold selection. To palliate this drawback, we introduce in the next section an evolutionary approach for automating the threshold selection and to make it specific for each building.

As shown in the workflow of the approach (figure 1), the proposed multi-agent system is made up of different types of agents: the supervisor agent, the NDVI agent, the edge agent and the region agent.

The functionalities of these agents are briefly summarized hereafter:

- **The supervisor agent** applies different techniques on the image to detect the corners of buildings, manages the life cycle of the other agents and their communications.
- **The NDVI agent** eliminates the vegetation pixels from the image.
- **The edge agent** has two distinct roles:
  1. *edge detection:* the pixels belonging to building's edges are detected using the method included in the agent. These edges are sent to the region agent to play the role of growing constraints.

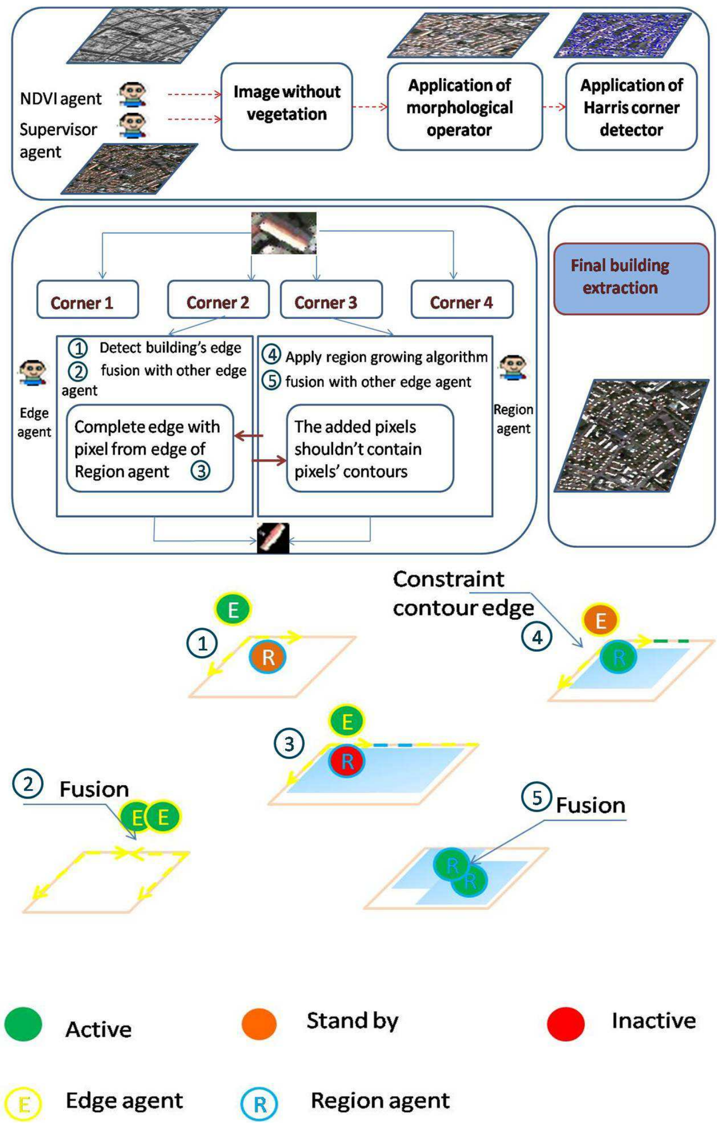


Fig. 1 Workflow of the proposed approach.

2. *edge correction:* completes the missed building edges based on the regions provided by the region agent and using the edges detected by the previous step (see 1).

– **The region agent**: a region growing algorithm is computed, driven by the edges sent by the edge agent, to detect the building regions. These results help the edge agent to detect the missing border pixels.

3.1 Pretreatment

Considering the variety of the satellite images content, it is necessary to apply a pretreatment step to eliminate the pixels which are not judged to be buildings. For this, the supervisor agent deploys an NDVI agent. It computes for each pixel the NDVI vegetation index (Crippen, 1990) given by:

$$NDVI = \frac{(NIR\ -\ VIS)}{(NIR\ +\ VIS)} \tag{1}$$

where VIS and NIR respectively stand for the radiometry measurements acquired in the visible (red) and near-infrared regions and returns to the supervisor agent the pixels judged as non-vegetation. The NDVI values usually range between -1 and 1. For example, a value of 0.5 indicates dense vegetation, whereas values less than zero imply no vegetation. Vegetation reflects both visible light and other radiation from invisible parts of the electromagnetic spectrum in unique ways (Myneni et al., 1995). To improve the contrast of the objects, especially for the roofs of the buildings and to correct irregular and discontinuous edges, the supervisor agent applies the morphological operator of dilation on the resulting color image using a rectangular structuring element. To apply an image color dilation, we can consider the colors as labels associated to each pixel or use the color values to establish a total ordering in the color space, which is the most used approach. In our case, we use this approach by applying the reduce ordering method (Comer et al., 1999). The guiding idea of the pretreatment step is to prepare the image and the starting points (i.e. building corner) for the agents of the building extraction step. Once the image is dilated, and based on specificity of the buildings which are characterized by a straight angles, the same agent uses the Harris detector (Harris and Stephens, 1988) to extract the corners in the image. In fact, the Harris corner detector is a popular interest point detector due to its strong invariance to rotation, scale, illumination variation and image noise. It is based on the local auto-correlation function of a signal; where the local auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different directions.

3.2 Buildings extraction

As already exposed in the related work section, there exist several approaches seeking to delineate objects in the image, including region-based and edge-based approaches. Both of them have advantages and drawbacks: the choice of the approach depends on the types and characteristics of the images. However, the use of these algorithms separately can give inaccurate results. For example, the Canny edge detection (Canny, 1986) provides mislocated buildings because it extracts all the edges without tacking into account the nature of the extracted object. In addition, many extracted buildings are incomplete. For the region growing algorithms, there is an obvious over-extraction i.e. false alarms which represent regions extracted from erroneous seeds Hence, combining these two approaches should be worth of interest to take advantage from the both. Moreover, we notice that in most cases, buildings contrast with their neighborhood and are homogeneous in terms of radiometry. This knowledge is not always valid. However, given the specificity of the buildings in the city of Strasbourg which imposes some construction conditions to maintain the homogeneity of the urban landscape, this hypothesis can be admitted in our agents conception. Heterogeneity cases will be treated with the fitness function in the next section. The supervisor agent starts the process by launching two agents from each detected corner (starting point) : an edge agent and a region agent. The region agent waits until the edge agent finishes its first processing based on the Canny edge detection method.

- from the current pixel, the agent seeks for candidate pixels not already treated in a 3×3 window by applying a gaussian smoothing and seeking gradients;
- based on the information that most buildings are contrasted with their neighborhood, are homogeneous and have a specific radiometry, the agent uses the Bhattacharya distance (Djouadi et al., 1990) to compute two distances to filter non-buildings edge pixels. The Bhattacharya distance,D_{bhat} , is a separability measure between two Gaussian distributions and is defined as follows:

$$\frac{1}{4(m_1 - m_2)^t(\Gamma_1 + \Gamma_2)^{-1}(m_1 - m_2)} + \frac{1}{2} ln \frac{\frac{1}{2}|\Gamma_1 + \Gamma_2|}{\sqrt{|\Gamma_1||\Gamma_2|}} \qquad (2)$$

  where m_i design the mean of radiometry and Γ_i the covariance matrix. The first term gives the class separability due to the difference between class means, while the second term gives the class separability due to the difference between class covariance matrices. Many studies compare the Bhattacharyya distance with other distances. They observe that Bhattacharyya yields better results and conclude that it is the most discriminate distance (Reyes-Aldasoro and Bhalerao, 2006).

The first one is the distance between the two windows used to detect an edge point as presented in Fig. 2.

The second Bhattacharya distance is computed according to expert knowledge represented in an ontology built during the FoDoMust project (Forestier et al., 2012; Sellaouti et al., 2012a,c, 2013). This distance is between a building window extracted by an expert and the two regions A and B shown in Fig. 2. This second distance determines if the current object is a building candidate or not. These two distances depend on two thresholds T_{edge} and T_{build}. The main problem is to define the adequate threshold to get the optimal building extraction. Experiments can provide a good thresholds but this choice is still image dependent. Then, when the edge agent completes the detection phase

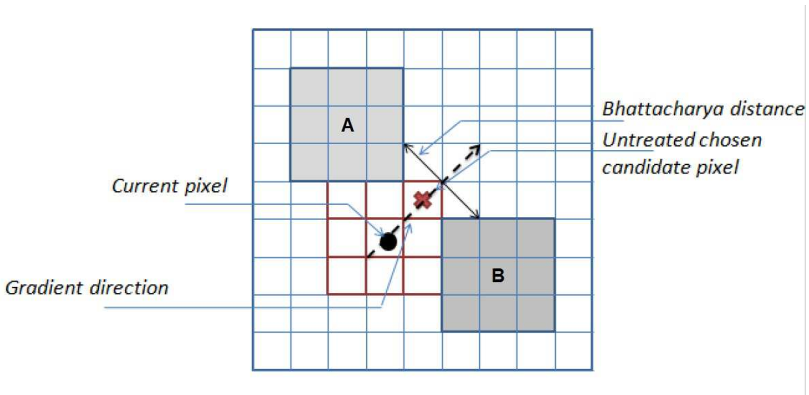


Fig. 2 Illustration of the calculation of the Bhattacharya distance between two regions A and B.

described above, it gives the hand to the region agent to finish the buildings detection, taking into account the results given by the edge agent as constraints for the region growing. The edge agent enters in "standby" phase until the region agent finishes its role. After that, with the help of the region growing results, the edge agent will be able to correct and to complete the missing buildings edge. The goal of the region agent is to help the edge region to determine missing edges.For that purpose, it grows from the building corner as long as the two following conditions are fulfilled:

- the added pixels should not contain border pixels;
- a pixel can be added to the area as far as it keeps the average homogeneity denoted T_{Hom}.

Once the region agent has finished the growing process, the edge agent finishes to delimitate the regions using the new pixels detected by the region agent and the old ones detected by its first step of edge detection. Along all the process, if an agent crosses with another agent of the same type, the two agents merge together to yield a new edge agent.The main drawback

of this approach is the choice of the different thresholds. Even when good parameters are detected, the parameter choice is still incomplete. In fact, as the objects in the image are different, the parameters used to optimize the buildings extraction differ from an object to another. To bridge this gap, we propose to use a local evolutionary approach.

4 Local evolutionary algorithm

In this section, we introduce our evolutionary local approach to detect the optimal parameters for each object in the image using the expert knowledge concerning the buildings. Several studies have already used genetic algorithms to optimize the parametrization of their approaches (Yang et al., 2011). The main contribution of our method consists in the local use of these algorithms. Figure 3 illustrates the proposed genetic algorithm. It aims to find the best individual which maximizing a fitness function $\mathbb{F}$. Let i be an individual (i.e. the genotype in the genetic framework) which is a vector composed by the three parameters $(T_{edge}, T_{build}, T_{hom})$ of our multi-agent system. The proposed genetic algorithm has an initialization step in order to choose a random initial population. Generally, the population size is an even value between 20 and 100 (Yang et al., 2011). Each individual represents a potential solution to our problem. Once the initial population is defined, each individual is evaluated using the fitness function $\mathbb{F}$. In this paper, the selection of individuals inside a given population is made by using the pattern "steady state" that selects randomly two parents by binary tournament and replaces the worst one by the best son generated by crossover. Then, we apply a mutation operator to each generation in order to preserve the population's diversity. This procedure allows to obtain the best results after nearly 30 iterations.

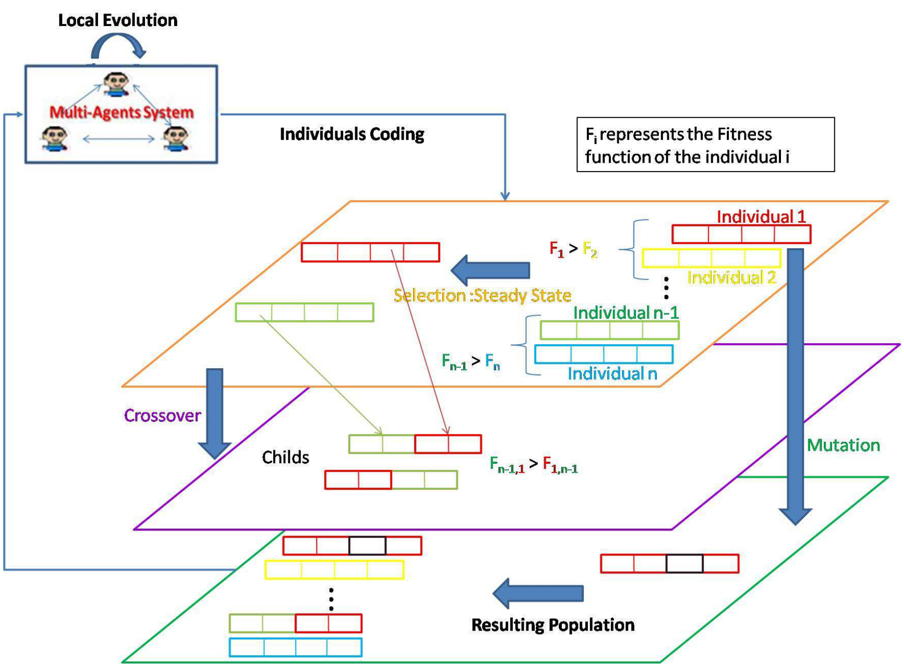


Fig. 3 Local Evolutionary multi Agent System

4.1 Definition of the fitness function

The fitness function associates to each individual a real value to measure its quality. In this work, our goal is to design a function that can give to each building on the image (associated to an agent) the optimal parameters set. We based our work on a set of expert knowledge describing buildings (Forestier et al., 2012) (area, rectangularity and homogeneity) to define this function (Eq. 3):

$$\mathbb{F}(i) = \mathbf{A}rea * (\mathbf{R}ec/(1 + \mathbf{H}om)). \tag{3}$$

Let $\mathbb{B}^i$=$\{b^i_j\}$ be the set of buildings extracted with the individual i. The area evaluation $\mathbf{A}rea$ is defined as:

$$\mathbf{A}rea = \begin{cases} 1 & if\ area(b^i_j) \in [min_{area}, max_{area}] \\ \frac{area(b^i_j)}{min_{area}} & if\ area(b^i_j) < \quad min_{area} \\ \frac{max_{area}}{area(b^i_j)} & if\ area(b^i_j) > \quad max_{area} \end{cases} \tag{4}$$

with $area(b^i_j)$ representing the area of the building (b^i_j) and min_{area}, max_{area}, respectively the minimal and the maximal area of a building, based on expert knowledge. The rectangularity evaluation $\mathbf{R}ec$ is given by an index (Toussaint, 1983) providing a measure of the rectangularity of a given region varying between 0 and 1. The homogeneity evaluation $\mathbf{H}om$ measures the standard deviation of the region. The fitness function favours regions having a high rectangularity with an area that belongs to the interval for specific buildings, and a high homogeneity characterized by a relative low standard deviation.

4.2 Selection operator

The selection operator defines individuals to improve the population. The main idea of this operator is to promote the best individuals by allowing them to transmit their genes to future generations. It mainly works at the level of chromosomes. Each individual is evaluated relies on its fitness function. Many selection methods are cited in the literature (Sivaraj and Ravichandran, 2011):

- i Proportionate Selection methods also known as roulette wheel selection. In this method, each individual has an opportunity to be selected proportional to its performance, which favors the most suitable individuals to problem. The major drawback of these methods is that it can cause a severe loss of diversity.
- ii Ranking Selection methods which are a variant of the first methods based on an a rank founded on fitness function of all the individual. These methods have the same problem of premature convergence.
- iii Tournament selection methods involves running several tournaments among randomly chosen individuals. The individual having the highest fitness value in each tournament is selected. With this intention, we choose the binary tournament method.

4.3 Crossover operator

During the crossover, the genetic information of the two parents (the parameters) are merged to create new individuals. Many crossover methods are proposed: one-point crossover, two-point crossover uniform crossover, half uniform crossover,.... (Beasley et al., 1993). In this work, we use the one-point crossover, in which each individual is divided into two parts, both children are created by merging the extracted parts of the two parents. The choice of the uniform crossover is due to the small number of parameters composing the used chromosome(3).

4.4 Mutation Operator

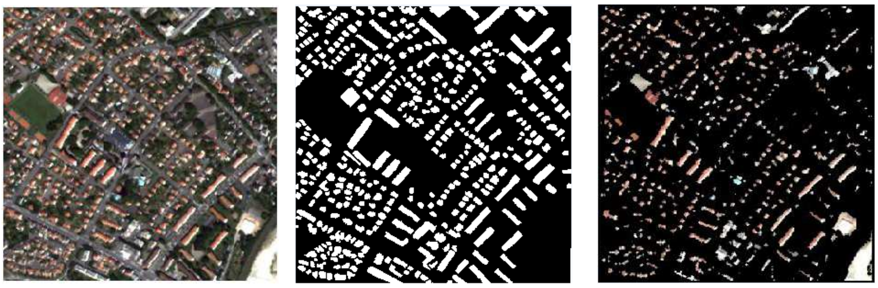
The mutation is a random deformation of the gene of one individual to preserve the diversity of the population and avoid local optimal. During the mutation, some genes of a random individual are changed. The probability of mutation should be small in order to let the population improve itself by crossover (Girgis et al., 2009). For that aim, we fix the mutation probability to 2%.

5 Experiments

We have tested our approach on a Quickbird image[1] covering an urban area of the city of Strasbourg, France (2008), having four spectral bands with a spatial resolution of 2.44m/px. To evaluate the performances of our approach, we used expert benchmark as shown in figure 4 which represent the site 4(a), the used expert benchmark 4(b) and the extraction result 4(c). We also tried it on a set of test areas selected by the geographer expert. The chosen examples represent a variety of context that appears in the image. This choice allows us to check the robustness of the approach with respect to changes in the characteristics of the image. Sites 5(a) and 5(e) represent sparse areas while site 5(b) is a dense region. Site 5(c) is a dense site with a lot of noise. The site 5(d) represent a variety of buildings with different shapes and sizes. The site 5(f) presents sparse area with a lighting problem. The detection images 6(a), 6(c), 6(e), 6(g), 6(i), 6(k) illustrate the extracted buildings, the white objects are the detected buildings. The superposition images 6(b), 6(d), 6(f), 6(h), 6(j), 6(l) show the exactness and the quality of the extracted building.

To show the extraction quality, we magnified a part of site 5(a). The figure 7(a) is the magnified part of the image and figure 7(b) is the magnified extraction result. Extraction results differ according to the density of the image and the noise in the image. The obtained results proof the robustness of our approach. However, the sparse sites present better results.

[1] provided by the LIVE laboratory of Strasbourg, France (ERL 7230)



(a) Site 1 (b) Expert Benchmark (c) Detection result

Fig. 4 Expert Image Extract and benchmark.

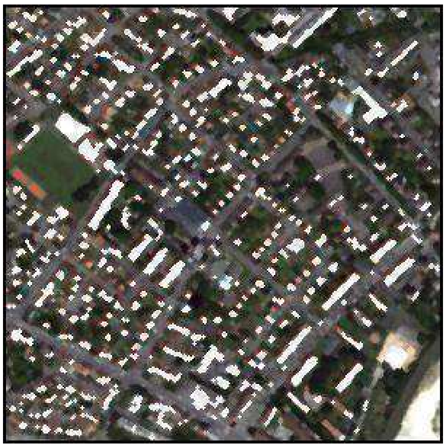
Figures 8(a),8(b),8(c) present extraction results during the genetic evolution. We observe an improvement of the buildings extraction and the number of extracted buildings increases along the evolution of the algorithm. The white objects presents the detected buildings.

(a) site 1 (b) site 2

(c) site 3 (d) site 4

(e) site 5 (f) site 6

Fig. 5 Strasbourg Quickbird test images (France).



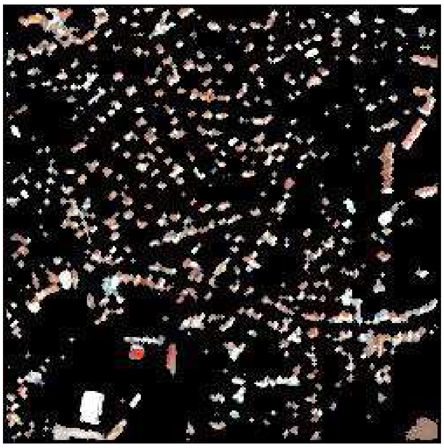
(a) superposition result site 1

(b) detection result site 1

(c) superposition result site 2

(d) detection result site 2

(e) superposition result site 3



(f) detection result site 3

(g) superposition result site 4

(h) detection result site 4

(i) superposition result site 5

(j) detection result site 5

(k) superposition result site 6

(l) detection result site 6

Fig. 6 Extraction Results

(a) Magnified extract (b) detection result

Fig. 7 Site 1 magnified extract.

(a) 10^{th} generation (b) 20^{th} generation (c) 30^{th} generation

Fig. 8 Building extraction results during a genetic evolution.

In the quantitative analysis, the objectives were to determine the practicability of the proposed approach whereby a building extracted percentage rate is calculated. The following metrics are computed (Rojbani et al., 2011):

$$BER = \frac{BCE}{(BCE + BPE + BNE)} * 100. \tag{5}$$

$$Exactness = \frac{BCE}{BCE + FA} * 100 \tag{6}$$

$$Excellence = \frac{BCE}{BCE + BPE + BNE + FA} * 100 \tag{7}$$

where BCE is the number of Building Correctly Extracted, BPE the number of Buildings Partially Extracted, BNE the number of Buildings Not Extracted and FA the False Alarms, representing the segments that are not really buildings but are identified as buildings.

The Building Extraction Rate (BER) is a measure of object detection performance, measuring the rate of objects correctly denoted as buildings by our system relies on expert benchmarks. The Exactness is a measure of delineation performance, measuring the number of objects that are true buildings from the number of objects extracted as buildings. Finally, the Excellence percentage combines aspects of both measures to summarize the system performance.

Table 1 presents the extraction rate for the six extracts from the set of test areas. We note that our approach is more effective and efficient for sparse image, but the results for the dense area remain quite satisfactory. The extraction rate reaches a 90%, and each building is clearly delimited.

Table 1 Quantitative Evaluation

sites	BCE	BPE	BNE	FA	BER	Exactness	Excellence %
site 1	249	6	18	31	91.20	88.92	81.9
site 2	220	10	19	19	88.35	92.05	82.08
site 3	192	9	14	27	89.3	87.67	79.33
site 4	95	6	7	12	87.96	88.78	79.16
site 5	89	7	6	11	87.25	89	78.76
site 6	78	9	7	12	82.97	86.66	73.58

Table 2 illustrates the results improvement along the evolution of the genetic algorithm of building extraction from site 2. As clearly mentioned in Table 2 the extraction results and the Excellence factor are exponentially rising with the number of iterations. Also, there is an amelioration in the exactness factor, it is not as high as the other factors but still represents an important evolution.

Table 2 Genetic algorithm improvement

Gen	BCE	BPE	BNE	FA	BER	Exactness	Excellence
10	85	120	20	8	37,77	0.89	0.34
20	145	66	15	17	64,15	0.92	0.62
30	179	16	10	25	87,31	0.94	0.86

For comparison, we have selected the ERE approach proposed by Erener (Erener, 2013). Erener use a pan-sharpening algorithm to improve the image quality. Then, he compares between the results of a SVM and MLC classifier and he proves that each algorithm is more suited to certain areas according to their specificities. We have taken care of choosing reference which use similar image features (Quickbird image) to our framework. However, the use of pan-sharpening algorithm improves the resolution of the multispectral image. Table 3 presents the comparison results of our approach and the ERE method.

The results show that, despite the ERE uses a pan-sharpening algorithm, our method is still very competitive and generates good results. In terms of extraction rate the average is about 87% which is better than the ERE. In terms of excellence our approach approximates the 90% and is also better than the ERE. This is due to the local treatment and the local use of the genetic algorithm for each object. For the exactness, the ERE presents better results, due to the use of a pan-sharpening algorithm that improves the image resolution.

Table 3 Numerical Comparison between The ERE (Erener, 2013) and our Evolutionary SMA method.

Approaches	Extraction results %	Exactness	Excellence
Evolutionary SMA	87.84	88.85	79.14
ERE (Erener, 2013)	77.19	96	75

6 Conclusion

In this paper, a cooperative multi-agent edge-region system for building extraction is presented. A local genetic algorithm is then introduced to improve the results of the system by permitting a local parametrization of the cooperation process and then resolving the threshold choice. Expert knowledge such as the shape and the area are used to guide the genetic evolution. To improve the extraction results we plan to use the pan sharpening algorithm to take advantages of both resolution of panchromatic band and color of multi-spectral bands.

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