An Agent-based Approach for Range Image Segmentation

Smaine Mazouzi[1], Zahia Guessoum[1], Fabien Michel[1], and Mohamed Batouche[2]

[1]MODECO-CReSTIC, Université de Reims, B.P. 1035, 51687, Reims, France
[2]LIRE, Département d'informatique, Université de Constantine
25000, Constantine, Algérie
mazouzi@leri.univ-reims.fr,zahia.guessoum@univ-reims.fr
fmichel@leri.univ-reims.fr,batouche@wissal.dz

Abstract. In this paper an agent-based segmentation approach is presented and discussed. The approach consists in the utilization of autonomous agents for the segmentation of a range image in its different planar regions. The moving agents perform cooperative and competitive actions on the image pixels allowing a robust extraction of regions and an accurate edge detection. An artificial potential field, created around pixels of interest, allows the agents to be gathered around edges and noise regions. The results obtained with real images are compared to those of some typical methods for range image segmentation. The comparison results show the potential of the proposed approach for scene understanding in range images regarding both segmentation performance, and detection accuracy.
Key Words: Image segmentation, Multi-agent systems, Range image, artificial potential field

1 Introduction

The segmentation of an image is often necessary to provide a compact and convenient description of its content, suitable for high level image analysis and understanding. It consists in assigning image pixels to homogenous and disjoint sub sets which form the regions of the image. The pixels which belong to a same region share a common feature called the region homogeneity criterion. In range imagery, segmentation methods can be divided into two distinct categories: Edge-based segmentation methods and region-based segmentation methods. In the first category, the pixels which correspond to discontinuities in depth or surface orientation are selected and linked in order to delimit regions in the image [7],[3],[9]. Edge-based methods are well known for their low computational cost, however they are very sensitive to noise.

Region-based methods use geometrical surface descriptors to gather pixels with the same proprieties in disjoint regions [20],[10],[12],[2]. Compared to edge-based methods, they are more stable and less sensitive to noise. However, their efficiency depends strongly on the selection of the region seeds. Often, the segmentation results in an over-clustering. So, it is necessary to perform an iterative fusion of homogenous regions. Such an approach does not facilitate the distribution of the used algorithms, and leads to high computational costs.

Furthermore, most of the proposed methods are based on the computation of local region proprieties by using image derivatives of different orders. Such techniques result in a high noise-sensitive detection. It is then necessary to perform some preprocessing tasks, which consist mostly in noise smoothing and filtering. However, in the case of highly noisy images such as range images [6], a strong noise smoothing can erase the roof edges, and smoothed edges whose detection remains a challenge. Moreover, if the noise is under-smoothed the distortions, which remain in the image, result in inaccurate or erroneous results. This difficulty, which is an open issue in image processing [15], results from the restriction of computation and decision to the local neighborhood of the processed pixel. In range imagery, several recent methods fail because they do not correctly address and resolve this problem [8].

To deal with this problem, agent-based solutions provide several advantages such as autonomy, proactivity, distribution, self-organization and adaptation. Agent-based solutions inherit the advantages of the agent-oriented systems for collective problem solving. In such systems a single agent has limited perception and capabilities, and it is not designed to solve an entire problem. The agents cooperate then in order to provide a collective solution. Contrary to conventional systems, solutions in agent-based systems emerge from collective actions within the population of the agents [11].

In this paper, a novel agent-based solution for range image segmentation is presented and discussed. It consists in the utilization of a dense population of reactive agents. The agents move over the image and act on the pixels. While moving over the image, an agent adapts to its planar region and memorizes its characteristics. When an agent finds a pixel which does not belong to its current region, an agent alters this pixel in order to align it to its current region. At the boundaries between regions the agents will be in competition to align the pixels of the boundaries to their respective regions. The resulting alternating alignment of the boundary pixels preserves the region boundaries against erasing. The noise regions that are characterized by small sizes or by random depth data prevent agents from adapting. Thus, these regions continuously contract by the alignment of their pixels to the planar regions which surround them.

Our aim is to overcome the difficulty related to the local perception around the processed pixel. A pixel is therefore processed according to both its neighborhood, and the agents that visit this pixel. The memory of an agent represents a larger perception. The combination of this perception with the image information provides more reliable decision. To optimize the agent movements, an artificial potential field inspired from the electrostatic potential field is used. It allows the rationalization the movements of the agents by directing them to be gathered around the regions of interest (edges and noise regions) and to concentrate their actions around these regions.

The utilization of a large number of reactive and weakly coupled agents provides a real massively multi-agent system. Extensive experimentations have been performed using real images from the ABW database [6]. The obtained results show the high potential of the proposed approach for an efficient and accurate segmentation of range images.

The remainder of the paper is organized as follows: In Section 2, we review the agent-based approaches for image segmentation. Section 3 introduces the surface features modeling. Section 4 is devoted to the proposed approach. It describes the behavior of the agents and shows the underlying collective mechanism to deal with the edge detection and the noise removal. The experimental results are introduced in Section 5, we discuss the selection of the used parameters, and we analyse and comment the obtained results. Finally, a conclusion summarizes our contribution.

2 Related work

Several agent-based systems have been proposed for image processing and object recognition. They propose interesting solutions to deal with several open issues such as multiple domain knowledge handling, control automation over the image interpretation tasks, and processing distribution and parallelization. In this review we consider only works which address solutions to image segmentation.

Liu et al. [14] introduce a reactive agent-absed system for brain MRI segmentation. They underline that the employed agents are more robust and more efficient than the classical region-based algorithms. Four types of agents are used to label the pixels of the image according to their membership grade to the different regions. When finding pixels of a specific homogenous region agents create offspring agents into their neighboring regions. In this system, the agents neither interact directly between them nor act on the image. Their actions depend only on their local perception. Nevertheless, each agent is created so that it becomes more likely to meet more pixels belonging to the region of its creator. For the same type of images, Richard et al. [17] propose a hierarchical architecture of situated and cooperative agents for brain MRI segmentation. Three types of agents have been used: global control agent, local control agent, and tissue dedicated agent. The role of the global control agent is to partition the volume of data into adjacent territories and to assign one local control agent to each territory. The role of a local control agent is to create the tissue dedicated agents which perform a local region growing. The statistical parameters of the image data distribution, needed to perform region growing are updated according to the interaction between neighboring agents. Using several types of agents has allowed to deal with both the control over the high-level segmentation tasks and the low-level image processing tasks.

The two previous systems are well adapted to the brain MRI and can provide interesting results because region characteristics are regular for the different brain anatomic parts. In addition, most of the edges in such images are jump edges which are easy to detect, compared to roof and smoothed edges.

Rodin et al. [18] introduce a multi-agent system made up of reactive agents for edge detection in biological images. This system is implemented by the multi-agent language oRis [5]. According to some priors on image content, the system provides an edge detection which is better than that the traditional one. Two groups of agents, called darkening agents and lightning agents follow respectively the dark regions and the light regions. Their actions aim at reinforcing regions by stressing their contrast, allowing a reliable detection of these regions. In this system, agents which follow different edges are fully independent from each other, and never interact. The system seems to be a parallel segmentation algorithm which was well optimized for the detection of roof edges in some biological images. However, it may fail to detect jump edges. Further, the number and the topology of the expected regions must be known and hard coded within the agents.

Based on the cognitive architecture Soar [16], Bovenkamp et al. [1] have developed a multi-agent system for IntraVascular UltraSound (IVUS) image segmentation. They aim to elaborate a high knowledge-based control over the algorithms of low-level image processing. In this system, an agent is assigned to every expected object in the image. Agents cooperate and dynamically adapt the segmentation algorithms, according to contextual knowledge, local information and personal believes. In this work, the problem of the control over segmentation algorithms seems to be well resolved. However, no agent or even behavior has been proposed to deal with the problem of uncertain and noisy data.

The proposed agent-based systems for image segmentation are specific to image contents. Following a supervised approach, these systems aim at segmenting images in known and previously expected regions. The system proposed in this paper claims to be general and unsupervised. It aims to segment an image into its several regions by using some invariant surface proprieties. The adaptive and competitive behavior of the agents allow overcoming the local perception constraints, inherent in image processing. We show in this work that despite the simplicity of the model used for data image representation, the obtained results are better than those obtained with conventional approaches. We believe that interactions between agents provide an alternative way for image segmentation to that of methods based on complicated and costly models [13].

3 Representation and Computation of Region Proprieties

A range image is a discretized two-dimensional array where at each pixel (x, y) is recorded the distance $Z(x, y)$ between the range finder and the corresponding point of the scene. Regions in such an image are the visible parts of the different surfaces. To attenuate the white and the impulsive noise contained in the image, a Gaussian filter and a median filter are applied to the raw data. a new image $Z^*(x, y)$, called relief image is then derived from the range image. Each pixel (x, y) of the new image records the tangent plane to the surface at (x, y). The best tangent plane at (x, y) is obtained by the multiple regression method using the set of neighboring pixels $\chi(x, y)$. The neighborhood $\chi(x, y)$ is made up of pixels (x', y') situated within a 3×3 window centred at (x, y), and whose depths $Z(x', y')$ are close, according to a given threshold (Tr_D).

The plane equation in a $3D$ coordinate system may be expressed as follows:

$$ax + by + cz = d \tag{1}$$

where $(a, b, c)^T$ is the unit normal vector to the plane $(a^2 + b^2 + c^2 = 1; c < 0)$ and d is the orthogonal distance between the plane and the coordinate origin. First, Parameters α, β and γ of the surface $z = \alpha x + \beta y + \gamma$ at (x_0, y_0) are obtained by the minimization of the function $\varPhi$, defined as follows:

$$\varPhi(\alpha, \beta, \gamma) = \sum_{(x_i, y_i) \in \chi(x_0, y_0)} [\alpha x_i + \beta y_i + \gamma - Z(x_i, y_i)]^2 \tag{2}$$

with

$\chi(x_0, y_0) = \{(x_0 + i, y_0 + j); (i, j) \in \{-1, 0, +1\}$ and $|Z(x_0 + i, y_0 + j) - Z(x_0, y_0)| < Tr_D\}$

Parameters a, b, c and d are thus obtained as follows:

$$(a, b, c, d)^T = \frac{1}{\sqrt{\alpha^2 + \beta^2 + 1}} (\alpha, \beta, -1, \gamma)^T \tag{3}$$

The tasks performed on the relief image are based on the comparison of planes. Indeed, we consider that two planes $ax + by + cz = d$ and $a'x + b'y + c'z = d'$ are equal if they have, according to some thresholds, the same orientation and the same distance to the coordinate origin. Let θ be the angle between the two normal vectors, and D the distance between the two planes: $\sin(\theta) = \|(a, b, c)^T \otimes (a', b', c')^T\|$ and $D = |d - d'|$. So, the two planes are considered equal if $\sin(\theta) \leq Tr_\theta$ and $D \leq Tr_D$, where Tr_θ and Tr_D are respectively the angle and the distance thresholds.

The test is first used to check if the pixel (x, y) belongs to a planar region, given its plane equation. It is also used to check if the pixel (x, y) is a pixel of interest (edge or noise pixel). In this case, the checked pixel is considered as a pixel of interest if at least one of its neighbors has a different plane equation, according the previous thresholds.

4 Proposed Approach

The relief image is considered as the environment in which agents are initialized at random positions. An agent searches a planar region around its current position, and adapts to this region by memorizing its plane equation. Next, the agent performs actions which depend on both its state and the state of the pixel at its location. At each time t, an agent is characterized by its position (x_t, y_t) over the image, and by its ability A_t to act on the encountered pixels. At the beginning of the process, all the agents are unable to alter the image pixels. An agent becomes able to modify a pixel (A_t=true) when it detects a planar region around its current position. When an agent alters a pixel, it loses its alteration ability (A_t=false) and starts again searching for a new planar region. An agent having modified a pixel records in an appropriate array I at the position (x_t, y_t) the last state of the visited pixel: $I(x_t, y_t) \in \{$smoothed, aligned, unchanged$\}$. We show next, that this simple behavior of the agents allow both the detection of the image edges and the removal of the noise regions.

4.1 Agent Behavior

An agent adapts to the region of the image on which it is moving by computing and storing the characteristics of this region and by adopting the suited behavior to the local image data. Fig. 1 depicts the behavior of an agent according to its state and the state of the pixel on which it is located.

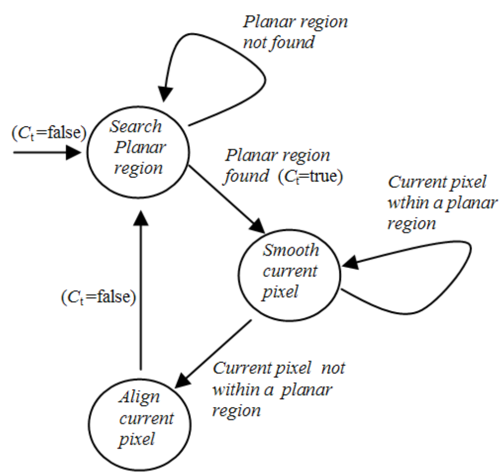


Fig. 1. Agent behavior according to its state and position

Searching for a Planar Region. After its creation, an agent randomly moves within the image and searches for a planar region around its current position. The seed of the searched region is formed of the last L pixels visited by the agent. L is called the readaptation path-length. It represents the confidence degree that the agent is situated within a planar region. The region seed is accepted if all its pixels form a planar surface. The agent memorizes the new region and considers it as its current planar region. The agent becomes then able to alter the first encountered pixel which does not belong to its planar region (A_t=true).

Moving on a Planar Region. While moving inside a planar region, an agent smoothes the pixel on which it is located by updating the equations of both the memorized plane and the plane at the pixel position. This is done by replacing the two equations by their weighted average. Let (a', b', c', d') and (a, b, c, d) be the parameters respectively of the memorized plane and the plane at the current pixel. Resulted parameters of the weighted average plane, before normalization, are obtained as follows:

$$(a'', b'', c'', d'') = \frac{1}{1+l}(a + la', b + lb', c + lc', d + ld') \tag{4}$$

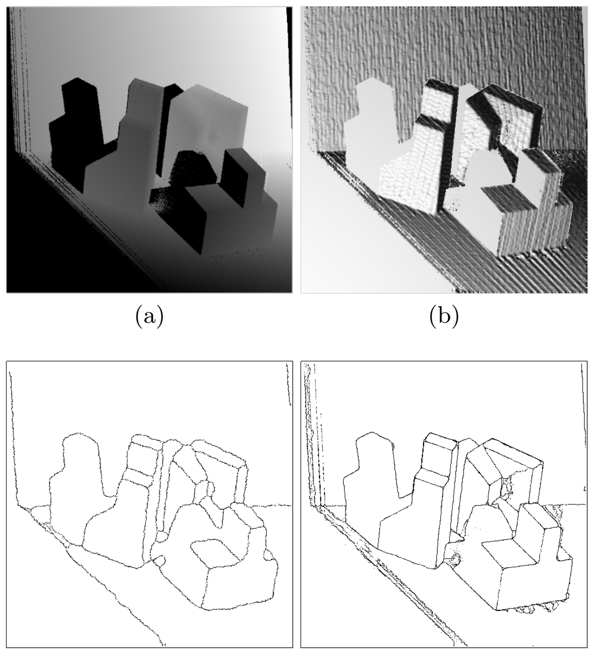
where l is the length of the path covered by the agent on the planar region.

Pixel Alignment. Pixels of interest are edge pixels or pixels within noise regions. When an agent meets a pixel which does not belong to its current planar region, it alters it in order to partially align it to the planar region on which it is moving. Parameters (a'', b'', c'', d'') of the new plane equation at the pixel position are obtained by linear combination of the old parameters (a, b, c, d) and the parameters of the memorized plane equation (a', b', c', d'):

$$(a'', b'', c'', d'') = \frac{1}{1+\xi}(a + \xi a', b + \xi b', c + \xi c', d + \xi d') \tag{5}$$

where ξ is the alteration strength.

After that, the agent looses its alteration ability (A_t=false) and starts again to search a new planar region. Further to the alteration of a pixel, the agent can pass into another region, or remain in the current region. If the altered pixel is an edge pixel, the agent likely pass in an other planar region. However, if the altered pixel is on the boundary of a noise region, the agent crosses the noise region and most likely will return to the previous planar region, except if the noise region is situated between two planar regions. The alteration strength ξ is a critical parameter which affects the quality of results and the time of computation. Indeed, high values of ξ lead to a fast detection of regions. However the resulted region boundaries are distorted and badly localized (Fig. 2c). low values of ξ result in a slow detection, but region boundaries in this case are well detected and correctly localized (Fig. 2d). In order to speed up the segmentation process and avoid edge distortion, an agent chooses the alteration strength among ξ_{min} and ξ_{max} according to the information recorded by other agents is the array I. Indeed, an agent assumes that the current planar region is adjacent to a noise region and thus uses ξ_{max} as alteration strength if there are at least 3 pixels labeled "unchanged" around the agent. Otherwise the agent assumes that the current planar region is adjacent to another one, were other agents have labeled the pixels as "smoothed" or "aligned". In this case the agent uses the alteration strength ξ_{min}.



(a) (b)

(c) (d)

Fig. 2. The impact of the alteration strength on the segmentation results: (a) Range image (abw.test.8); (b) Rendered range image; (c) Segmentation results with $\xi_{min} = \xi_{max} = 4$ at t=2500; (d) Segmentation results with $\xi_{min} = 0.3$ and $\xi_{max} = 5$ at t=13000

4.2 Agent Coordination by Artificial Potential Field

An electrostatic-inspired potential field is created and updated around altered pixels. It allows agents to be gathered around pixels belonging to region boundaries. Contrary to other works, where the potential field is created at known positions of objects (goals and obstacles) [4], [19], the potential field in our case results from the interaction of agents with the objects in the environment (image pixels). The intensity $\Psi(x, y)$ of the potential field at position (x, y) created by a set of P pixels beforehand altered $\{(x_i, y_i), i = 1..P\}$ is given by:

$$\Psi(x, y) = \sum_{i=1}^{P} \frac{k}{\sqrt{(x - x_i)^2 + (y - y_i)^2}}, k \in R^+ \tag{6}$$

where k is the constant of the electrostatic force.

An agent which is able to alter pixels (A_t=true) and situated at position (x_t, y_t) undergoes an attractive force $\overrightarrow{F}$. This force is expressed thanks to the gradient vector of the potential field:

$$\overrightarrow{F} = \begin{cases} -\overrightarrow{\nabla}\Psi(x_t, y_t) & \text{if } A_t\text{=true} \\ \overrightarrow{0} & \text{otherwise} \end{cases}$$

So, the agent movements, which are stochastic in nature, are weighted by the attractive force applied by the potential field. Agents are influenced to head for the pixels of interest, while keeping random moves. The latter allow the exploration of all regions of the image.

A Relaxation mechanism of potential field is also introduced. It allows the agents gathered around pixels of interest to be released and thus to explore other regions of the image. Around a given pixel, the field intensity decreases after every alteration of this pixel. The relaxation dynamic equation is expressed as follows:

$$\Psi_{t+1}(x, y) = \mu \times \Psi_t(x, y), \mu < 1 \tag{7}$$

$\Psi_0(x, y)$ corresponds to the created field after the first alteration of the pixel. The constant μ set to 0.9, represents the decrease rate of the field intensity. After several alterations of a given pixel, the field intensity around this pixel decreases and tends to zero. This situation represents the final state of the process.

4.3 Edge Detection and Noise Removal

While moving over the image, agents smooth pixels that approximatively belong to the current planar region. An agent considers pixels that do not belong to this region as noise pixels. The latter pixels are thus automatically aligned to the current planar region. However, pixels on the boundaries of planar regions are true-edge pixels and thus should not be aligned. Nevertheless, these pixels will be preserved thanks to the competition between agents. Indeed, around the edge between two adjacent planar regions, two groups of agents are formed on the two sides of this edge. Each group is formed by agents that transit from one region to another. Agents of each group align the pixels of the boundary to their current region. So, pixels of the boundary are continuously swapped between the two adjacent regions. This allows these pixels to be emergent in the image. This pattern of competitive actions between agents allows the emergence of image edges. The edge map is not coded in any agent, it results from the collective actions and interaction of the agents.

Unlike true regions of the image, which remain preserved against erasing, sizes of noise regions continuously decrease and they finally disappear. Borders of these regions are continuously aligned to the true surrounding planar regions. An agent, having aligned a pixel which belongs to the border of a noise region and having transited inside this region, will not be able to adapt. Consequently, it cannot align any pixel when leaving the noise region. This occurs in two distinct situations: 1) when a region is planar but insufficiently large to allow agents to cross the minimal path-length L necessary to be able to adapt; 2) when a region is sufficiently large but not planer, or made up of random depths (noise). In both situations, the agent leaves the noise region and will adapt inside the surrounding planar one. True regions have thus sufficiently large size to allow agent to adapt and then align boundary pixels when leaving these regions. However, noise regions, which are non planar or having weak size, prevent agents from adapting. Consequently, agents will be unable to align pixels on the boundaries of these regions when leaving them. In this case, boundaries of these regions are continuously aligned from outside by including their pixels in the true surrounding regions. After several execution steps, these regions will be completely erased.

5 Experiments and Analysis

5.1 Evaluation Framework

An evaluation framework dedicated to range image segmentation has been proposed by Hoover et al. [6], and has been used in several works related to range image segmentation [9], [8], [12], [2]. The framework consists of a set of real range images, and a set of objective performance metrics. It allows comparing a machine-generated segmentation (MS) with a manually-generated segmentation, supposed ideal and representing the ground truth (GT). The most important performance metrics are instance numbers respectively of correctly detected, over-segmented, under-segmented, missed, and noise regions. Region classification is performed according to a compare tool tolerance T; $50\% < T \leq 100\%$ which reflects the strictness of the classification. The 40 real images of ABW set were divided into two subsets: 10 training image subset and 30 test image subset. The training images are used to estimate the parameters of a given segmentation method. Using these parameters, the method is applied to 30 test images.

Values of the different performance metrics are computed and stored in order to be used to compare the different methods. We use four methods : USF, WSU, UB and UE, cited in [6] in our comparative study.

5.2 Parameter Selection

For our System, named 2ARIS for Agent-based Approach for Range Image Segmentation , six parameters should be set: ξ_{min}, ξ_{max}, Tr_θ , Tr_D, N, and L. These parameters are divided into two subsets: 1) ξ_{min}, ξ_{max}, Tr_θ, and Tr_D represent respectively the two alignment strengths, and thresholds of the angle and the depth. These parameters are used for checking and aligning image pixels, and 2) N and L represent respectively the number of agents, and the readaptation path-length. These two parameters control the agent dynamic. For the first parameter subset, 256 combinations namely (ξ_{min}, ξ_{max}, Tr_θ, Tr_D) $\in \{0.5, 0.3, 0.1, 0.05\} \times \{1.0, 3.0, 5.0, 7.0\} \times \{15, 18, 21, 24\} \times \{12, 16, 20, 24\}$ were run on the training images. The performance criterion for this parameters is the average number of correctly detected regions with the compare tool tolerance T=80%. The two alignment strengths ξ_{min} and ξ_{max} are set respectively to 0.3 and 5.0. These values have provided a good edge detection in a reasonable execution time. The threshold Tr_θ was set to 20. We have observed that higher values of this parameter under-differentiate pixels and lead to an under-segmentation of the image. However, lower values over-differentiate pixels and lead to an over-segmentation. It results in a high number of false and small regions, which should be merged in the true adjacent regions. Finally, the threshold Tr_D is set to 16. Values significantly less than 16 can lead to erroneous fusion of some parallel overlapped regions. However, if Tr_D is significantly higher than 16, high sloped regions cannot be detected as planar regions [**?**]. This results in a high rate of missed regions.

The number of employed agents N, and the readaptation path-length L are critical and must be carefully selected. Inappropriate values of these two parameters can lead to a high rate of segmentation errors. Indeed, an insufficient number of agents lead to an under-processing of the image. So, resulting regions are deprived of a set of pixels which should be included in these regions. A low value of the readaptation path-length L leads to take into account small planar regions which should be considered as noise regions. However, higher values of L can result in missing some true planar regions which are insufficiently large (see section 4.3). In order to set the parameters N and L, 25 combinations of these parameters, namely $(N, L) \in \{1500, 2000, 2500, 3000, 3500\} \times \{3, 5, 7, 9, 11\}$ were run on the training set. In this case, the performance criterion is the average number of noise regions, with the compare tool tolerance set to 80%. Optimal values of N and L are respectively 2500 and 7.

5.3 Experimental Results

Fig. 3 shows an instance of segmentation progression within time. The time t represents the number of steps performed by each agent since the beginning of the process. Displaying a range image by a simple rendering algorithm (Fig. 3a), allows observing the high level of noise in the used images. Figures 3b, 3c, 3d and 3e show the set of pixels of interest (edge or noise pixels) respectively at t=1000, 5000, 9000 and 13000. Regions are progressively smoothed by aligning noise pixels to their surrounding planar regions. Edges between adjacent regions are also progressively thinned. At the end of the process, contours are made up of thin lines of one pixel wide (Fig. 3e).

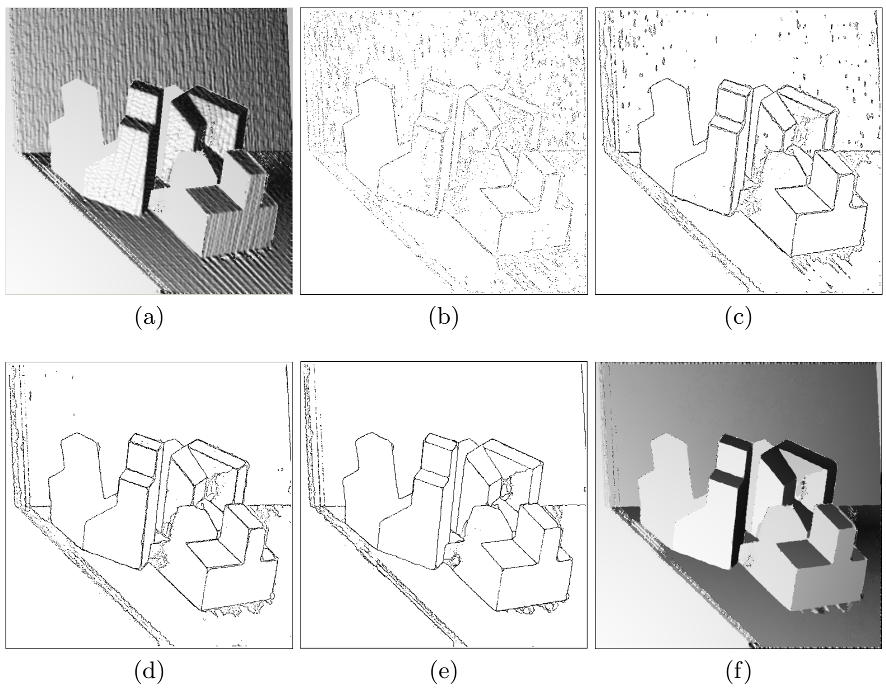


Fig. 3. Segmentation progression. (a) Rendered range image (abw.test.8); (b) at t=1000, (c) at t=5000 ; (d) at t=9000 ; (e) at t=13000 ; (f) Rendered resulting range image

Table 1 introduces the average results obtained with all the test images for all performance metrics. The compare tool tolerance was set to the typical value 80%. Regarding both correct detection and incorrect detection metrics, obtained results show the good efficiency of our system. Fig. 4 shows the average numbers of correctly detected regions for all the test images at different values of T; $T \in$ {51%, 60%, 70%, 80%, 90%, 95%}. Results show that the number of correctly detected regions by our system is in average better than those of USF, UB and WSU. For instance, our system scored higher than WSU for all the values of the compare tool tolerance T. It scored higher than USF for $T \in$ {80%, 90%, 95%}, and better than UB for $T \in$ {50%, 60%,70%, 80%}. For all incorrect detection metrics (Over-segmentation, Under-segmentation, Missed, Noise), our system has equivalent scores to those of UE and USF. The latter score higher than UB and WSU.

Table 1. Average results of the different involved methods with T=80%

Method	GT region	Correct detection	Over-segmentation	Under-segmentation	Missed	Noise
USF	15.2	12.7	0.2	0.1	2.1	1.2
WSU	15.2	9.7	0.5	0.2	4.5	2.2
UB	15.2	12.8	0.5	0.1	1.7	2.1
UE	15.2	13.4	0.4	0.2	1.1	0.8
2ARIS	15.2	12.9	0.5	0.1	1.7	0.9

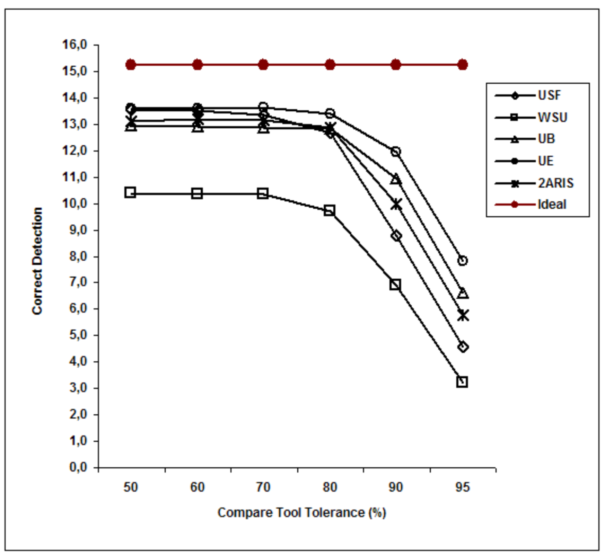


Fig. 4. Average results of correctly detected regions of all methods at different compare tool tolerance T ; $0.5 < T \leq 1.0$

6 Conclusion

In this paper we have introduced an agent-based approach for range image segmentation. Indirect interaction between autonomous agents moving over the image allows efficient noise removal, and reliable edge detection. Competitive actions between agents that are self gathered around region boundaries have allowed the emergence of image edges. Image edges for which any explicit detection has not been coded in agents, result thus from the collective action and interaction of the whole agents. The proposed approach aims to improve efficiency and to deal with the problem of result accuracy. Indeed, obtained results are better than those provided by traditional algorithms, based on region growing techniques. Moreover, employed agents are weakly coupled, and indirectly communicate via the environment (image). This allows distributed implementations, necessary to obtain a high computational efficiency. Experimental results obtained with real images from ABW database were compared to those provided by four typical algorithms for range image segmentation. Comparison results show a good potential of the proposed method for both segmentation efficiency and accuracy.

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