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A potential field-based multi-agent model for contour detection in range images

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Abstract

In this paper, we propose a reactive potential-based multi-agent system for edge detection in range images. A population of situated agents is launched to explore the image. While moving, each agent smooths the image along its path and alters points which do not belong to surface on which it moves. On the border between two adjacent surfaces, two groups of agents will be in competition to include border points into their respective surfaces. This competition will preserve contours against erasing. However, noise is erased by successive smoothing operated by agents moving on the same surface. A potential field, created around the altered points, allows the agents, moving in the neighborhood, to concentrate their actions around these points. After several alterations of the same point, the potential field around it is relaxed, allowing, agents which were under its influence, to be released and explore other areas of the image.

1. Introduction

Due to their complex acquisition methods, and to the surface orientations of the contained objects, range images are considered extremely noisy [13]. Several approaches have been proposed to segment range images [6]. Unfortunately, traditional methods, which are based on the examination of the immediate neighborhood of the treated pixel do not provide satisfactory results and, thus do not lead to a reliable interpretation of the image content [4,6]. The Gaussian or impulsive noise, which characterizes the images produced by a given range sensor, makes the contour detection in such images more or less reliable [9]. Indeed, if the image is highly noisy, strong smoothing can lead to erase the object contours [10]. However, if

the image is not sufficiently smoothed, the remaining noise makes contour detection ineffective and sullied with errors. To remedy the problem of local vision of image content, inherent to traditional methods, several works proposed agent-based systems for image processing and understanding [12]. These systems inherit the advantages of the agent-based approach for problem resolution. This approach consists in collective and distributed problem solving. In such a system, a stand-alone agent, for lack of general competence or global data, cannot solve the problem in its entirety. Thus, the agents have to cooperate in order to overcome their individual insufficiency. Contrary to non multi-agent based systems, the dynamical agent interactions in agent societies lead to the emergence of a global solution. Rather, some traditional segmentation algorithms have been reinterpreted using agent technology. For instance, in split and merge algorithm, agents correspond to regions, and reassigning pixels from one region to another can be considered as a cooperative negotiation scheme [12].

In this paper, we propose a multi-agent system for both image smoothing and contours detection in range images. In contour detection, one of the difficulties is that criteria for edge point differentiation can not be trivially defined and verified. In order to overcome this difficulty, we introduce a competition scheme between antagonistic agent groups, where the system dynamic leads to contour detection. Used images represent scenes containing polyhedral objects. While moving, agents smooth the image at points along their paths. When an agent encounter a point does not belong to its surface, the point is altered in order to better align it to the surface. Isolated points which do not belong to any surface or points gathered in small numbers will disappear after several smoothing iterations which are performed by an agent group moving on the surrounding surface. However, points situated on a

border between two adjacent surfaces will be alternatively modified by the two groups of agents which move on the two sides of the border. So, the contour is preserved against erasing. The use of a potential field for agent cooperation [2,14] around altered point allows gathering agents and so, to concentrate treatments on the contour lines and noise regions. The principle of our approach, compared with other approaches, consists in agent competition to modify the points of interest in the image. This competition allows the emergence and the enhancement of contours as well as noise erasing.

The remainder of the paper is organized as follows: Section 2 presents the works which have proposed multi-agent systems for image segmentation. Section 3 gives an overview of the proposed approach and describes the behaviors of our agents. In section 4, we show how the potential field is used to provide an efficient agent spatial coordination mechanism, allowing an indirect cooperation scheme. Sections 5 and 6 show respectively the resulted mechanism of collective contour detection, and the mechanism of noise removal. Section 7 provides some experimental results and comparison results with some published range image segmentation methods. We conclude the paper by summarizing the proposed system and showing the possible extensions of this work.

2. Related works

Several works have used agent-based systems for image segmentation. J. Liu and Y. Y. Tang [7] proposed a system for brain MR Image segmentation. Their approach uses four types of agents to label image pixels according to their membership values to the four predefined regions. Agents which succeed in recognizing their referred regions create other agents and place them according to some preferred directions. These directions increase the chance that the created agents meet new pixels of the same referred region. V. Rodin et al. [11] proposed a multi-agent system for rings detection in images with specific contents. Two types of agents, based on BRIC formalism [2], allow following lighten rings and darken rings. Their actions aim to reinforce rings by stressing the contrast in order to allow a reliable future detection of these rings. In [5], the authors use a massive multi-agent system, to implement an FCM-based region growing algorithm. The fusion of adjacent regions is performed according to the negotiation between agents which hold these regions. Fernandes et al. [3] use artificial ant colonies for contour point localization in a grey level image. The movements of the ants (agents) are stochastic,

weighted by the pheromone deposited beforehand by other ants, having detected non similar close areas. Y. Wen and Y. Q. Chen [1] proposed an evolutionary artificial life algorithm for image segmentation. Agents are placed in the image which is considered as an ecosystem. They are organized in tribes and exchange local properties of the image in their neighborhood. The aim of the agent evolution is to minimize the intra variability of any tribe and to maximize the inter variability between the various tribes. S. Mazouzi et al. [8] have proposed a multi-agent system for contour detection and edge reconstruction using a population of autonomous agents. The smoothing parameters were automatically adapted according to the organization which is established within the agent population.

Contrary to works listed below, which use other agent interaction schemes, the model proposed in this work, introduces a competition scheme between antagonistic agent groups. We show, along the paper, that the agent group competition, allow contour enhancement and emergence. Potential field based spatial coordination, used in this work, enables processing optimization, by self agent gathering around interesting image regions.

3. The Proposed multi-agent system

For our system, the environment in which agents evolve is a relief image. Each point of this image represents the best tangent plane of the surface at this point according to the least square method. A population, of a greater number of agents, is launched in the image. Used agents have a low granularity and a reactive behavior. They are initialized in arbitrary positions in the image.

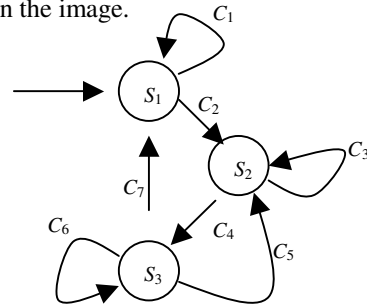


Figure 1. Agent behaviors. States: S_1 : reference surface searching, S_2 : surface exploration, S_3 : point alteration. Conditions: C_1 : reference surface not found, C_2 : NOT C_1 , C_3 : current point belongs to reference surface, C_4 : NOT C_3 , C_5 : positive energy and current point belongs to reference surface, C_6 : positive energy and current point does not belongs to reference surface, C_7 : null energy.

Each agent is characterized by its current position in the image and by its energy acquired during moving on a planar surface. While evolving an agent memorize its current surface and considers it as its reference surface. According to its energy and to its position, each agent exhibits several behaviors. Figure 1 shows the different behaviors of an agent and conditions for which it topples between these behaviors.

3.1. Searching for a reference surface

After its creation, an agent randomly moves in the image and searches for a first homogeneous region which will be its current reference surface during the future exploration. The seed of an agent reference surface is a set of neighbor points situated on a planar surface. With this intention, the agent examines the neighborhood around its position and counts the number N_0 of points having roughly the same tangent plane. The agent acquires an initial energy E_0 proportional to the planarity degree of its reference surface seed. It is defined as follow:

$$E_0 = \sum_{i=1}^{N_0} \delta_E \times q_i \quad (1)$$

δ_E and q_i represent respectively the energy gain at each step and the quality of the plane estimation factor, regarding the least square method, at the point i .

3.2. Surface exploration

Without the influence of the potential field, an agent randomly moves on its surface of reference. Along its path, and in order to increase the homogeneity of its surface, the agent smoothes the points on its path by using an average filter applied to the tangent planes at the traversed points. The average plane equation of the reference surface is continuously readjusted according to traversed points. Along the path on its reference surface an agent accumulates energy. Energy supply at each step is $\delta_E \cdot q$, where q is the quality of the estimated plane at the current point. The accumulated energy E upper bounded by E_{max} , represents the adaptation degree of the agent to its surface of reference. It determines the agent capability to alter the points which do not belong to its surface of reference. The accumulated energy determines also the force intensity applied to an agent by the potential field (see section 4). The agent direction is stochastic but influenced by the attractive force of the potential field which induce the agent to move towards the non aligned points which were reached beforehand by other agents.

3.3. Contour or noise point alteration

When an agent meets a point not belonging to its reference surface, it modifies the encountered point so that this point will be roughly aligned to the surface of reference by computing the average plane at this point. After the execution of this task, the agent loses a part, $\lambda \delta_E$, of its energy. The constant λ , ($\lambda \gg 1$) represents the loss to gain ratio of energy. For our experimentations the factor λ was chosen so that an agent can alter only one point, so $\lambda = E_{max} / \delta_E$.

3.4. Agent adaptation to a novel surface

An agent loses the whole of its energy when it moves towards another surface. It becomes unable to modify points on its path. At this stage, a process of readaptation is started within the agent. This process consists in agent adaptation to the current surface on which it is situated and considers it as its new surface of reference. This mechanism is necessary to ensure alteration equilibrium of a boundary independently of the surface areas. Indeed, with two adjacent surfaces having significantly different sizes; agents moving on the biggest surface will invade the second one. So, the border between the two surfaces will moves towards the interior of the surface having the smallest size, and this latter will disappear after a high number of iterations. (Fig. 2).

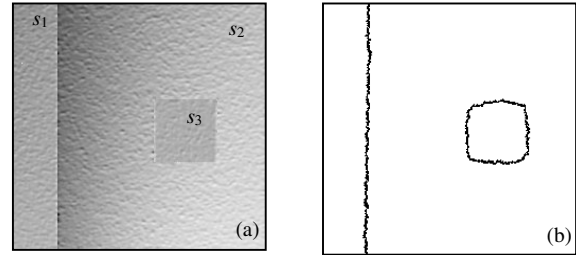


Figure 2. a) Range image with three surfaces s_1, s_2 and s_3 . b) Contour detection using a group of 500 agents (without readaptation), the smallest surface, s_3 starts to narrow.

4. Agent cooperation via potential field

An artificial potential field inspired from the electrostatic potential fields, is created around altered points. Contrary to other works where the potential field is created according to known positions of objects, the field which we use results from the interaction of the agents with the objects of the

environment. At any point having coordinates (x,y) , the intensity of the field $\Psi(x,y)$ created by a set of N previously altered points $(x_{0,i},y_{0,i})$, $\{i=1..N\}$ is calculated as follows:

$$\Psi(x, y) = \sum_{i=1}^N \frac{k \times (1 - q_i)}{\sqrt{(x - x_{0,i})^2 + (y - y_{0,i})^2}}, k \in R^+ \quad (2)$$

Where k is the electrostatic force constant, and q_i the plane estimation quality at point $(x_{0,i},y_{0,i})$.

An agent situated at the position (x,y) having an energy E , equivalent to the load in the electrostatic field, undergoes a force calculated by the gradient of the potential field as follow:

$$\vec{F} = \begin{cases} -E \times \vec{\nabla} \Psi(x, y), & \text{if } E > E_{\text{infl}} \\ \vec{0}, & \text{else} \end{cases}, E_{\text{infl}} \in R^+ \quad (3)$$

E_{infl} is an energy threshold expressing the agent sensitivity to potential field. An agent does not undergo any force if its energy is lower than this threshold. Indeed, this will allow the agents having lost all their energy to be released from attractive forces, and so searching for a new surface on which they will be readapted. The stochastic direction of an agent is influenced by the attractive force of the potential field.

A mechanism of relaxation of the field is introduced in order to allow agents to be released and explore other regions of the image. At a given point, the field intensity decreases after each alteration of this point. The relaxation dynamic equation is defined as follow:

$$\Psi^{(t+1)}(x, y) = \xi \times \Psi^{(t)}(x, y), \xi < 1 \quad (4)$$

$\Psi^{(0)}(x, y)$ corresponds to the created field after the first alteration. The constant ξ denotes the decrease rate of the field intensity. After several alterations, the field generated by the same point becomes insignificant. At the dynamic limit, the potential field is full-relaxed in the whole image. This represents the final state of the dynamic, after which the system is stopped.

5. Contour emergence

The goal of each agent consists in smoothing the image by aligning points which do not belong to its associated surface. These points can be, unfortunately,

really contour points. Nevertheless, at the border between two adjacent surfaces, agents will be in competition situation. Indeed, agents moving on one of the two surfaces align the points of the border in order to include them in their associate surface. However, agents moving on the second surface make similar, but include points in their own surface. Thus, the points of a border are altered by one group of agents and restored by the other. A task of object contour thinning is also performed. The points of external edge sides are continuously aligned to the surface on which the agents operate. The points in the middle of the band, which represents a thick edge, will be preserved due to the competition of the two groups of agents operating on the two sides of the edge (Fig. 3).

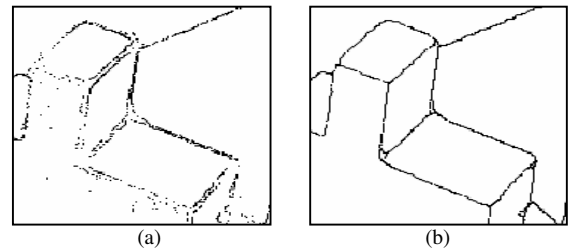


Figure 3. Contour thinning by agent competition. a) resulted contours at 800 iterations, b) resulted contours at 8000 iterations.

At the dynamic convergence, the contour points between two adjacent surfaces will be seen rocking continuously between the two surfaces. It results an emergent structure produced by the competition of the two groups of agents in order to include the points of contour in their respective surfaces.

6. Noise removal

Agents exploring the image smooth the noise areas on their path and lose their energy when crossing the contours. However, and contrary to true object surfaces, any agent having spent its energy to smooth noise points will not have sufficient area, in the traversed noise region to be readapted. So, it will leave this region and will be self readapted in the surface surrounding the noise region. According to the detail level of image content, a threshold Δu_s determines the minimal distance traversed by an agent to have space to be self readapted to a given surface.

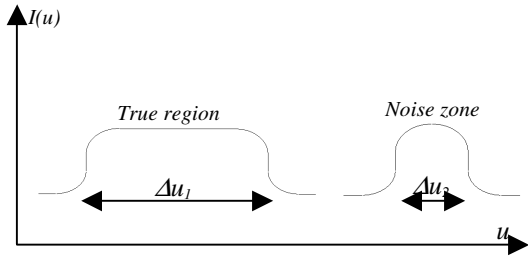


Figure 4. True object surface and noise region lengths.

Figure 4 shows image function variation of both a true object surface and a noise region. The length Δu_1 which represents the size of a true object region, is higher than the threshold Δu_s . So, the agents which move in this surface will have sufficient space to be readapted, and will smooth the image by including points to the surface while leaving it. However, agents which move into noise region (Fig. 4), traverse a distance Δu_2 lower than the threshold Δu_s . In this case, agents will not have sufficient space to be readapted to this region. They leave the area without altering its contours. In other words, true surfaces of objects have sufficient area to allow agents to be readapted and then smooth borders by including points into these surfaces. So, the surfaces are preserved to disappear by consecutive smoothing. However, noise regions which are characterized by weak areas, do not allow agents to be readapted. Borders of these areas are continuously smoothed from outside by including their points in the surrounding regions. After several iterations these regions will disappear.

7. Experimental results

The proposed approach was tested on real images from ABW sensors. These images were used in segmentation comparison projects [6]. Each image represents a scene containing polyhedral objects in visual occlusion. Initially, a spatial smoothing of the image, by an average filter is performed. In a second stage, an image of relief is calculated. In this novel image, each point is represented by the best tangent plane to the surface at this point according to the least square method.

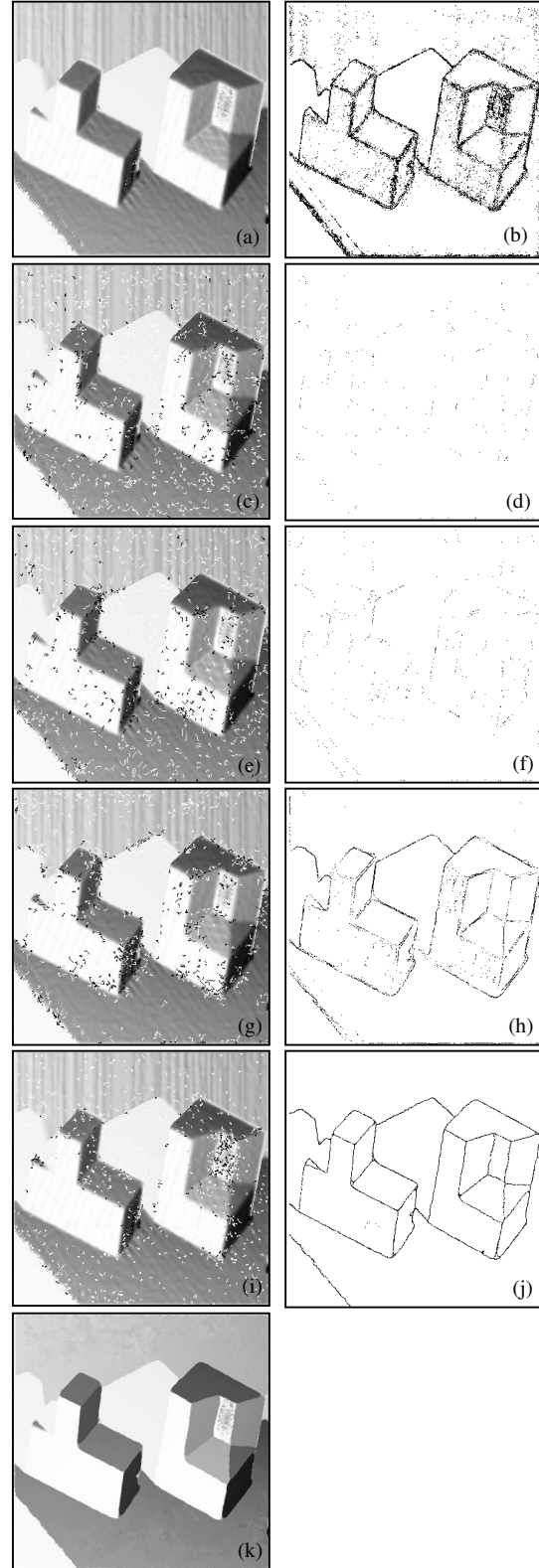


Figure 5. Dynamic evolution, contour detection and noise smoothing results.

After several tests using a subset of real range images, parameter values were chosen as follows: energy gain $\delta_E=1$, the upper bound energy $E_{\max} = 100$ and the noise region length threshold $\Delta u_s = 7$. This latter value does not allow agents to be adapted if their path length in a novel crossed region is lower than this threshold. This value corresponds in fact, to the smallest size of a true surface in the image. Any area whose dimensions are lower than this value will be considered as a noise region and will be completely erased at the end of treatments. Values of parameters E_{infl} and ξ , which control the potential field dynamic, are respectively 20 and 0.01. These values are empirically determined according to both image size, nature of the noise, as well as the level of detail of objects which are contained in the treated images.

Figure 5 shows an example of the dynamic evolution of the system. A 360x360 range image was used (Fig. 5.a). It was illuminated by a simple ray tracing algorithm using the orientation of the normal vector to the surface to calculate the corresponding grey level value. A population of 1000 agents was used. Figure 5.b shows the detected contour using direct computation of normal vector variation. Due to the high level of noise present in the image, the obtained result is unsatisfactory and not exploitable. We have presented this result to allow comparison between the direct use of a detection operator and the use of the same operator by the proposed multi-agent system. Figures 5.c and 5.d show the state of the agents and the set of altered points after 20 iterations. At this stage, no agent is under the influence of the potential field, although some points were altered and thus generated potential fields around them. Figure 5.e and 5.f show the first influence of the field at 200 iterations. At this stage the attracted agents have cumulated an energy E higher than the threshold E_{infl} . After 800 iterations, clusters of agents were formed (Fig. 5.g , 5.h) around regions of interest (contours and noise regions) under the effect of the potential field. Figure 5.i shows the state of the system after potential field relaxation in the whole of the image. The final detected contours obtained at 8000 iterations are shown in figure 5.j. At this stage the agents move according to stochastic directions free from any influence. Figure 5.k shows the new state of object surfaces and contours. The noise was highly smoothed and the contours were enhanced and thinned.

In order to evaluate the performance of our system, we carried out a comparative study by using the framework proposed in [6]. This framework is conceived especially for performance evaluation of algorithms for range image segmentation. Our results

were compared with those produced by three algorithms, which are [6]: USF algorithm from University of South Florida, UB algorithm from University of Bern, Switzerland and UE algorithm from University of Edinburgh, Scotland.

The comparison results obtained after reproducing segmentation results of the considered algorithms, on 19 images with variable complexity, allow us to compare the ratios of correct detection of the various algorithms, according to the error tolerance threshold T . Table 1, shows the various values of the average ratio of correct detection, according to the tolerance threshold T . Figure 6 shows a comparison graphic allowing locating the performance of the considered systems according to the correct detection ratio.

Table 1. Average correct detection values according to the tolerance error threshold T .

Tolerance (T)	USF	UB	UE	Proposed System
0,50	85,33	78,67	83,11	91,67
0,60	84,89	77,78	80,44	90,35
0,70	84,89	76,00	80,44	89,04
0,80	76,00	75,56	77,78	81,14
0,90	52,44	61,78	64,00	53,51
0,95	25,33	39,56	41,33	28,51
1,00	0,00	0,00	0,00	0,00

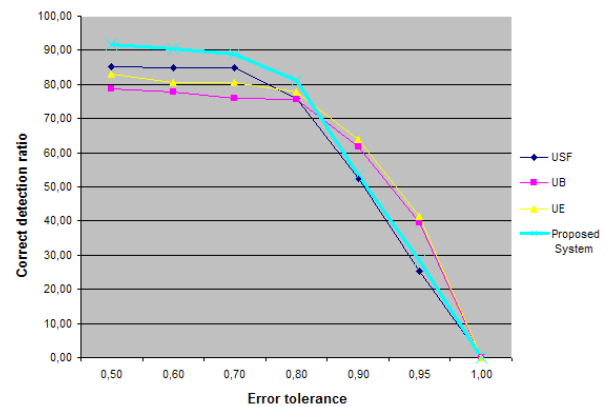


Figure 6. Correct detection comparison

8. Conclusion and perspectives

In this paper we have proposed a potential field-based multi-agent system for contour detection and noise smoothing in range images. A great number of agents were used. The agents have a low granularity and stochastically move in the image. Noise regions

are erased by successive smoothing performed by a group of agents moving on surfaces surrounding these regions. However, the competition of two agent groups evolving of the two sides of a contour preserves this contour against erasing. In order to get the system to speed up a cooperation mechanism between agents via a potential field was introduced. The potential field is created around points which are altered by agents. The potential field around a given area influences the agents which are in the neighborhood to move towards the points which are to be aligned and situated in areas requiring a concentration of agents. The relaxation mechanism of the potential field allows the agents to be released and explore other areas of the image for searching new regions which must be treated. The proposed system can be extended to be used to other types of images. For that it is necessary to define homogeneity criteria of image regions, and to define the various used parameters which are best appropriate to the types of treated images.

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