

# The Channeler Ant Model: Object Segmentation with Virtual Ant Colonies

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**Abstract**—3-D object segmentation is an important and challenging topic in computer vision that could be tackled with artificial life models. A Channeler Ant Model (CAM), based on the natural ant capabilities of dealing with 3-D environments through self-organization and emergent behaviours, is proposed. Ant colonies, defined in terms of moving, pheromone laying, reproduction, death and deviating behaviours rules, is able to segment artificially generated objects of different shape, intensity, background. The model depends on few parameters and provides an elegant solution for the segmentation of 3-D structures in noisy environments with unknown range of image intensities: even when there is a partial overlap between the intensity and noise range, it provides a complete segmentation with negligible contamination (i.e., fraction of segmented voxels that do not belong to the object).

## I. INTRODUCTION

ANT Colony Models are computational simulations of ant colonies that use the behaviour rules observed in nature to design cooperation/competition strategies to be put in place by virtual agents: the emergence of a global *smart* behaviour can be exploited to solve difficult problems. Successful applications of Ant Colony Models range from optimization techniques [1], [2] to swarm robotics [3]. The use of Ant-Colonies in image processing, pattern recognition and object segmentation started in the nineties [4]. Many solutions for 2-D image segmentation, thresholding and processing were developed but few of them were used in a 3-D environment

[5]–[8]. However, Ant Colonies in nature are intrinsically 3-D, since all the activities performed by an ant super-organism, like forging, larvae feeding, nest building, etc. take place in a 3-D environment [9]. The approach we propose, called *Channeler Ant Model*, is a stable and elegant solution that requires little tuning (parameter-wise), provides an excellent performance on images with different dynamic ranges and noise levels and opens a multitude of possibilities for further research. The present work was carried on within the MAGIC-5 Project [10], focused on the development of algorithms for the automated detection of anomalies in medical images. The *Channeler Ant Model* discussed here will be adopted as a tool for the analysis of lung CT scans, so as to segment and remove the background coming from the bronchial and vascular trees in the lungs, which is the biggest source of false positives in the automated search for nodules.

Social insects form a decentralized super-organism composed of many cooperative, independent, sensory-motor equipped components that are spread in the environment and respond to external stimuli based on local information that can come either from the environment itself or from other nest mates. The perception of the colony is the sum of perceptions of all its members, while the colony behaviour is the sum of all the interactions between the ants and the environment and between themselves.

### A. Ants in Images

Chialvo and Millonas [4] introduced one of the simplest and most efficient models of trail forming when the ants are not moving in a closed boundary and are not suppressed by other behavior rules. They compared the *trail leaving* technique with the cognitive map patterns from brain science, with the difference that ants leave their trails in the environment while the "mammalian cognitive maps lie inside the brain". Based on the above paper, Ramos and Almeida [11] developed an extended model where a constant population of ants is deployed in a digital habitat (i.e., an image) that the insects perceive and in which they move: they showed that ants are able to react to different types of digital habitat, achieving in the end a global perception of the image as the sum of the local perceptions of the single colony members. In the model evolution [12], [13] a mechanism that self-regulates the population by using the concepts of ageing, death and reproduction in the ant colony is described. The work of Ramos and Almeida is at the root of the model we present

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in this paper. The literature provides many examples of ant colonies implementations in 2-D images based on different algorithms: ant colony systems, perceptual graphs and binary trees ([7], [8], [14]–[16]). Unfortunately few of them are scalable or can be applied in 3-D imaging.

## II. THE CHANNELER ANT MODEL

The deployment of ant colonies in 3-D images could in principle be very effective whenever complex connected structures, with several ramifications of different size and intensity, must be identified and reconstructed, as long as a general model with few requirements on parameter tuning is designed and validated on images with known properties (different signal to background ratio and intensity range). The development of the *Channeler Ant Model* (CAM) was triggered by the idea of using it for the search of suspect nodules in Lung Computed Tomographies: the CT analysis will use the CAM model to segment the bronchial and vascular tree and remove it from the CT before the search for nodular structures in the image with a dedicated filter.

### A. The Colony Members

The behaviour of ants, partially derived from [4] and [11], is described in terms of four modules: the *moving* rules, the *pheromone laying* rules, the *reproduction/death* rules and the description of the ant response to anomalies (*deviating behaviour*). Ants explore (*i.e.*, "live in") a 3-D spatial environment described in terms of the properties (position, intensity) of discretized VOlume ELements (*voxels*) and their life cycle is defined in terms of atomic time steps, during which ants move from one *voxel* to a neighbour. So, at time  $t$  an ant  $k$  is in *voxel*  $v_i$ ; after one life cycle (time  $t + 1$ ) it will move to *voxel*  $v_j$ . In a 3-D environment, a *voxel* has 26 first order neighbours according to Moore's neighbouring law [17]. Two types of individuals live in a colony: the *queen* and the *worker* ant. The *queen* acts as an observer, performing tasks related to the colony coordination such as deciding when an ant dies or new ants are born. The *workers* carry out the nest building (*i.e.*, the objects segmentation): they move in the habitat and lay pheromone according to its properties.

### B. The Ant Colony Rules

The behaviour of *worker* ants is defined by a set of rules that specify how they move in the environment, how much pheromone they release before moving to another location, when they reproduce or die, how they react to anomalies (*e.g.*, when they reach the environment boundaries): the modelling of each of these rules is discussed in the following subsections.

The environment is essentially defined by the *voxel* image intensities, which can be thought of as the amount of available food for the colony: therefore, *voxel* intensities should be progressively consumed when the number of visits increases. This mechanism, required to make the colony evolve and explore the environment, is implemented in a complementary way: whenever the limit to the maximum number of visits ( $N_V$ ) in a *voxel* is reached, the *voxel* is no more available as a destination.

1) *The Moving Rules*: Randomness is an important factor in self-organization as it can assure a good balance between following a well established path and the probability of finding new and better paths, triggering the exploration of new regions of the environment. The random component associated to the way an ant walks in nature is taken into account for the choice the future destination. However, the choice of the direction for a step must also take into account the colony global knowledge of the environment, which is provided by the amount of pheromone already released in a given position ( $\sigma_j$ ). The pheromone laying rules are analysed in the following, but the meaning of a pheromone message is the same as in nature: a large amount of pheromone in a candidate destination must correspond to a high probability of becoming the actual destination. Ants make one step per life cycle: therefore an ant  $k$  located in *voxel*  $v_i$  at time  $t$  must select its destination. The choice is made according to the following rules:

- only the  $n = 26$  first order neighbours are destination candidates;
- for each *voxel* neighbour  $v_j$ , a probability  $P_{ij}$  for it to be chosen as destination is computed;
- if an ant is detected in  $v_j$ ,  $P_{ij}$  is set to zero;
- once a probability of becoming the future destination is assigned to each candidate, one of them is selected by a roulette wheel algorithm.

The probability  $P_{ij}$  that a candidate destination is chosen is defined as follows:

$$P_{ij}(v_i \rightarrow v_j) = \frac{W(\sigma_j)}{\sum_{n=1,26} W(\sigma_n)} \quad (1)$$

where  $W(\sigma_j)$  depends on the amount of pheromone in *voxel*  $v_j$  and the denominator is a normalization factor. The pheromone-related term  $W(\sigma_j)$ , taken from [4], depends on the *osmotropotaxic sensitivity*  $\beta$  (the larger it is, the larger the influence of the pheromone trail in deciding the ant's future destination) and on the sensory capacity  $1/\delta$  (if the pheromone concentration is too high, it will determine the decrease of the ant's capability of sensing it):

$$W(\sigma_j) = \left(1 + \frac{\sigma_j}{1 + \delta \cdot \sigma_j}\right)^\beta \quad (2)$$

A random number selected in the  $[0, 1]$  interval determines which *voxel* is actually selected as destination.

2) *Pheromone Laying Rules*: According to the biological laws of ant colonies, before moving to the future destination an ant  $k$  deposits in the *voxel* it is about to leave a quantity of pheromone  $T$ , defined as [11]:

$$T = \eta + \Delta_{ph} \quad (3)$$

where  $\eta$  is a small quantity of pheromone that an ant would leave anyway and  $\Delta_{ph}$ , the differential quantity of the pheromone, links the image properties to the pheromone habitat in which the ants live. Its value is a *voxel*-intensity dependent function:

$$\Delta_{ph} = \Psi(I) \quad (4)$$

The choice of the depositing rule is very important as it is related to the type of segmentation the ants are going to

perform. Some possible choices of  $\Delta_{ph}$  for an ant that moves from *voxel*  $v_i$  to  $v_j$  with intensities  $I(v_i)$  and  $I(v_j)$  are shown below:

$$\text{Rule I} - \Delta_{ph} = \text{const} \cdot I(v_i) \quad (5)$$

$$\text{Rule II} - \Delta_{ph} = \text{const} \cdot |I(v_i) - I(v_j)| \quad (6)$$

$$\text{Rule III} - \Delta_{ph} = \text{const} \cdot \frac{\sum_{l=1}^{n'} I(v_l)}{n'} \quad (7)$$

where  $n'$  is the total number of neighbours including the starting *voxel*:  $n' = n + 1 = 27$  since only first order neighbours are considered. *Rule I*, in which the ant lays a quantity of pheromone directly proportional to the intensity of its starting *voxel*, is used for object segmentation; *Rule II* can be used for border detection, while *Rule III* can be used for segmenting homogeneous regions.

After depositing the pheromone according to the implemented rule, the ant moves to the selected destination *voxel*.

3) *The Life Cycle - Reproduction and Death*: Ants, like all the living creatures, live for a finite amount of time. The life cycle is regulated by a parameter called energy [13], which is assigned at birth with a default value:

$$\varepsilon_0 = 1 + \alpha \quad (8)$$

The energy variation must take into account the properties of the environment, which are defined by the deposited amount of pheromone  $\Delta_{ph}^k$  for the current cycle and by the average amount of pheromone per step the colony has deposited since the beginning of its evolution, used as a normalization factor ( $< \Delta_{ph} >$ ). Therefore, the energy variation is defined as follows:

$$\varepsilon_{t+1}^k = \varepsilon_t^k - \alpha \cdot \left(1 - \frac{\Delta_{ph}^k}{< \Delta_{ph} >}\right) \quad (9)$$

The energy range is defined by a lower limit, the death energy  $\varepsilon_D$  and an upper limit, the reproduction energy  $\varepsilon_R$ : an ant with energy  $\varepsilon_t^k$  will die whenever  $\varepsilon_t^k < \varepsilon_D$  and give birth whenever  $\varepsilon_t > \varepsilon_R$ . In that case, the ant energy is reset to the default starting value  $\varepsilon_0$ . The ant life cycle duration is therefore a function of the ratio between the rate of the energy variation ( $\alpha$ ) and the amplitude of allowed energy range ( $\varepsilon_R - \varepsilon_D$ ), all of it modulated by the properties of the environment. The number of ants that are generated when a reproduction takes place ( $N_{offspring}$ ) must be related to the local properties of the environment and take into account the number of free destination *voxels* ( $n_f$ ).

The local properties of the environment are evaluated by smoothing the 3-D image with the average of its 125 second order neighbours:

$$I_5(v_i) = \frac{1}{125} \sum_{x_i, y_i, z_i = -2, 2} I(x_i, y_i, z_i) \quad (10)$$

The number of generated ants can be an integer in the (1,26) interval: the actual number  $N_{offspring}$  is determined assuming that it linearly depends on  $I_5$ , with  $N_{offspring} = 0$  (26) corresponding to  $I_5 = I_{5,min}$  ( $I_{5,max}$ ) respectively:

$$N_{offspring} = 26 \cdot \frac{I_5(v_i) - I_{5,min}}{I_{5,max} - I_{5,min}} \quad (11)$$

In case  $N_{offspring}$  is larger than the number of free neighbours  $N_{free}$ , it is set to  $N_{free}$ .

4) *The Deviating Behaviours*: Some conditions, not compatible with the above-described rules, require the definition of the allowed *deviating behaviours*. In particular:

- when an ant is fully surrounded by fellow mates and any possible destination *voxel* is unreachable, the ant is killed;
- when an ant reaches the border of the habitat it is killed.

### C. Deploying the Model

The Channeler Ant Model, discussed in the previous section, can be easily translated into an algorithm for 3D image segmentation, which hereafter is referred to as the *CAM algorithm*. It is worth pointing out that the CAM algorithm output is not a segmented image but rather a pheromone map, which can be considered an effective preprocessing of the 3D volume for the actual segmentation, which is discussed in the following and it is actually provided by the analysis of the pheromone map. The Ant Colony evolution goes as follows:

- initially, at  $t = 0$ , all the *voxels* are pheromone free: no information to the ants is available for their evolution;
- an initial ant-hill is chosen in a *voxel* that belongs to the structure to be segmented and  $G$  ants are released in all directions with default energy;
- the ants start moving around in the environment according to the above described CAM rules and deposit pheromone;
- the selected rule for depositing pheromone is defined with the goal of segmenting high intensity regions:  $\Delta_{ph} = \text{const} \cdot I(v_i)$ , where  $I(v_i)$  is the intensity of the *voxel* on which the ant stands;
- a cycle is finished when all the ants in the population have made one move;
- after a cycle is completed, the ants energies are updated and compared to  $\varepsilon_D$  and  $\varepsilon_R$ ;
- if a death is triggered then the ant is killed and the number of members in the population updated;
- if an offspring takes place, the newborn ants are placed randomly in free neighbouring *voxels* with default energy and the colony population is updated;
- the colony lives and moves until no more ants are alive or until the user-predefined number of cycles has been completed;
- once the colony evolution stops the 3-D pheromone map is stored and analyzed.

## III. TESTING THE MODEL

### A. The Artificial Images

The task of a CAM colony is to provide 3-D pheromone maps of the explored volume, to be used as a starting point for the segmentation of structures. In order to assess the model performance, it is important to study its results on a set of artificially generated 3-D objects with different shape, known properties (intensity distribution, background level). The results we present were obtained with a set of objects with heterogeneous intensity extracted from a gaussian with  $\mu_I$  average and  $\sigma_I$  standard deviation and a background noise extracted from a gaussian with  $\mu_{noise}$  average and  $\sigma_{noise}$

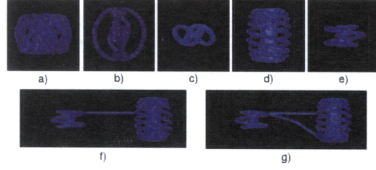


Fig. 1. The Artificial Objects Shapes used for the model validation: a) the toroid, b) the knot, c) the highway, d) the yo-yo, e) the scale, f) the 1-Arm bridge, g) the 2-Arm bridge.

standard deviation. The implemented shapes, shown in fig. 1, were selected to test the model behaviour in different conditions: the *highway* tests that ants truly channel in 3-D; the *scale*, *knot*, *toroid* and the *yoyo* test the channeling through an object that constantly changes orientation; the *bridges* define the colony reaction to thin multi-branch structures.

#### B. Parameters Optimization

The colony evolution is a function of several parameters that describe:

- the way an ant computes the perceived pheromone quantity from a *voxel*, based on equation 2 that contains two parameters:  $\beta$  and  $\delta$ . The ants are supposed to have a chance of either following the pheromone trail or to keep going on their initial orientation: in [11] the authors discovered the emergence of well defined networks of trails with  $\beta = 3.5$ ,  $\delta = 0.2$ , the values we decided to adopt.
- the way an ant deposits pheromone in the *voxel* it is about to leave, set according to equation 3. The default quantity of pheromone that an ant leaves behind ( $\eta$ ), which only certifies a *voxel* was visited, must be small: it is defined in such a way that it is always negligible with respect to typical pheromone releases when the intensity is larger than zero:

$$\eta = 0.01 \quad (12)$$

- the way the ant energy is updated, according to equations 8 and 9:  $\alpha$  is a constant that ensures that each ant makes at least a few moves before dying, while the scale factor that determines how quickly the energy of an ant will increase or decrease, thus deciding how fastly the reproduction and death take place, is defined in terms of the local habitat properties.

The critical issue is related to the necessity to find a satisfactory equilibrium between two different effects: the capability to explore new, pheromone free volumes and the minimization of the so-called *tunneling*, which causes ants to reach unconnected high intensity volumes.

The maximum number of steps travelled by an ant in a pheromone free region is given by:

$$N_{steps} = (\varepsilon_R - \varepsilon_D)/\alpha \quad (13)$$

In order to minimize *tunneling*,  $N_{steps}$  must be small. In the present work, the  $\varepsilon_D$ ,  $\varepsilon_R$  and  $\alpha$  parameters were

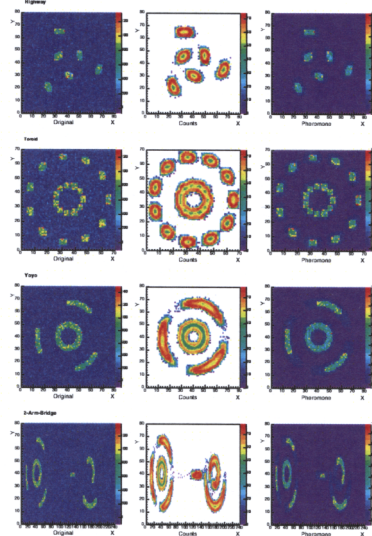


Fig. 2. Channeler Ant Model results on some objects: a) 2-D slice of the original image, b) 2-D map of *voxels* visits, c) 2-D section of the pheromone map. Row 1: the *highway*, row 2: *toroid*, row 3: *yoyo*, row 4: *2-Arm-Bridge*. The columns show the intensity of a 2D slice in the original image, the number of visits received by the ants and the amount of pheromone released, respectively.

set to 1.0, 1.3, 0.2, respectively: therefore, in pheromone free areas, no more than two steps can be travelled.

The limitation to the number of visits a *voxel* can receive ( $N_V$ ), introduced in order to make the colony evolve in time along the structures to be segmented, is not to be considered a model parameter. Its upper limit defines the speed with which structures are segmented, not the capability of ants to segment them. The lower limit must take into account that the number of visits a *voxel* receives is also related to the exploration of its surroundings: since the definition of the ants future destination is probability-based,  $N_V$  must be large enough to allow a statistically significant number of moves to all the neighbours of any visited location. In other words,  $N_V$  is *voxel*-dependent and inversely proportional to the average intensity in the surrounding volume, so that in low intensity areas a larger number of visits is allowed, increasing the statistical significance of the results.

#### IV. RESULTS

Once the model parameters were optimised, the CAM was deployed on the artificial objects set. The CAM performance was tested as a function of the object intensity (average and standard deviation) and background dispersion (i.e., noise).

Each time an ant colony life cycle is completed, a 3-D pheromone map of the original image is available for the analysis, as well as a 3-D map of the number of visits each *voxel* received: fig. 2 shows some samples of 2-D slices for the different object shapes.

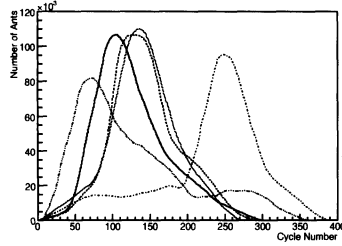


Fig. 3. Number of ants as a function of the cycle number for the segmentation of the *2-Arm-Bridge* starting from different anthill positions. The ant colony evolution pattern is different, as expected, but the *sensitivity* and the *exploration level* are compatible and show that the CAM performance does not depend on the anthill location.

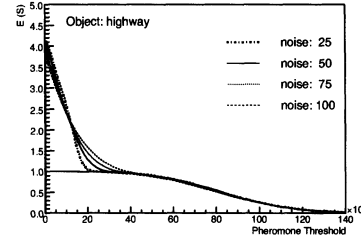


Fig. 4. *Exploration Level* ( $E$ ) and *Sensitivity* ( $S$ ) for the *highway* (average intensity 700, standard deviation 200) as a function of the selected pheromone threshold for different noise values. The *Exploration Level* is maximum at zero threshold, then it decreases until it merges with the *Sensitivity*, when it is still very close to 1. The merging value of the pheromone threshold increases, as expected, with the noise value.

The analysis of 3-D pheromone maps for the definition of the segmentation performance will be described in detail later on.

#### A. Colony Evolution

The population colony evolution is an interesting marker of the dynamical behaviour during the exploration process. The evolution pattern is usually simple, with a triangular-like shape. However, when the anthill is placed along a thin long structure, the peak structure appears later, since the population growth is prevented until the ants reach the thicker parts of the object.

The colony life duration depends on the object complexity and size as well as on the anthill position (for example, the *1-Arm-Bridge* is the last to be completed because the anthill is placed on the thin arm structure). The colony evolution is also a function of the anthill location: depending on the local object properties (i.e., the topology in the surroundings of the anthill), the number of ants in the colony shows different patterns, as seen in fig. 3. The peak in the ant population is always reached when the thick arm structures are explored. When the anthill is located on (or close to) the thin bridge connecting the two arms, the population reaches a plateau, corresponding to the bridge exploration, and increases again when the ants reach the arms.

#### B. Object Segmentation

In order to evaluate the CAM performance with respect to the object segmentation, a definition of when *voxels* are to be considered as part of the object must be provided. We chose to use an *inclusion condition* that, applied to the pheromone map, generates a binary image: whenever a *voxel* contains more pheromone than a predefined threshold value ( $Ph_{th}$ ), it is classified as *segmented*. Therefore, the results are threshold dependent and, in principle, shape dependent.

The following analysis will show that the CAM provides shape-independent results as well as the possibility of defining a common threshold for the pheromone map analysis, which makes it suitable for the analysis of complex structures with *a priori* unknown intensities.

In order to quantify the model performance the following quantities are defined:

- *Sensitivity*:  $S = N_R/N_O$ , i.e. the ratio between the number of correctly segmented *voxels* and the number of *voxels* in the original object, after the pheromone map analysis;
- *Exploration Level*:  $E = N_V/N_O$ , i.e. the ratio between the number of visited *voxels* and the number of *voxels* in the original object;
- *Contamination*:  $C = N_C/N_O$ , i.e. the ratio between the number of segmented *voxels* that do not belong to the original object and the number of *voxels* in the original object, after the pheromone map analysis.

According to the definitions:

$$C = (N_V - N_R)/N_O = E - S \quad (14)$$

$S$ ,  $E$  and  $C$  are function of the threshold value: however, if the model is general enough, they shall not be object shape dependent.

The results described in the following are compatible for all the shapes and prove that the model is general enough to segment different objects with the same sensitivity and exploration levels.

The *Exploration Level* and *Sensitivity* for the *highway* at different noise levels are shown in fig. 4: while the *Sensitivity* is almost unaffected, the *Exploration Level* smoothly increases with increasing noise values. As expected, the *Exploration Level* is maximum at zero threshold and decreases as the threshold increases. Higher values of the noise standard deviation turn into a higher merging threshold value for  $E$  and  $S$ .

The effect of an increasing intensity range on the *Exploration Level* and *Sensitivity* is shown in fig. 5 for the *2-Arm-Bridge*. Higher average intensities turn into higher values of the maximum pheromone threshold for which a 100% *Sensitivity* is achieved with a roughly linear correlation; on the other hand, there is no effect on the *Exploration Level* in the low intensity region.

The CAM behaviour as a function of the noise and of the average intensity shows that, unless the noise levels are very

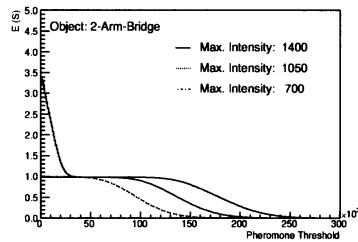


Fig. 5. Exploration Level ( $E$ ) and Sensitivity ( $S$ ) as a function of the selected pheromone threshold for the 2-Arm-Bridge with increasing average intensity, with constant standard deviation, noise and baseline. The plateau at  $E S 1$  is wider as the average signal intensity increases.

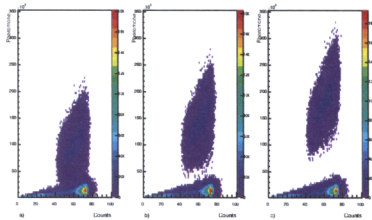


Fig. 6. Pheromone Level ( $Ph$ ) as a function of the Number of Visits (Counts,  $N_{Vis}$ ) for the 2-Arm-Bridge with constant standard deviation, noise and baseline at different average intensity: 700 (a), 1050 (b), 1400 (c). The 2D correlation shows that it is possible to improve the Sensitivity by selecting a pheromone threshold which depends linearly on the number of visits.

high, it is possible to define a range of pheromone threshold values for which the segmentation is fully satisfactory, i.e. that  $E S 1$ . Moreover, as seen in fig. 6, the pheromone level in and the number of visits to a *voxel* are correlated in a different way for the object and the background: therefore, in case of large noise values, it is possible to define a more effective *voxel* selection rule.

## V. CONCLUSION

Artificial ant-colonies have been used in image processing for over a decade, but most of the existing algorithms and models deal with 2-D image segmentation, thresholding or processing problems. Since real-ants in nature perform unknown, uncharted object recognition every day and they carry on 3-D object construction in the activity of nest building, artificial ant colonies should be able to do the same. The Channeler Ants Model describes ants in terms or rules that define their moving capabilities, the pheromone release, the life cycle (birth, reproduction, death) and the deviating behaviours and proves to be suitable for a full segmentation of objects of different shape, intensity range in a noisy background. The property of channeling appears as an emergent behaviour of the entire colony, which propagates in the 3-D image, its population being controlled by the energy depletion, until the full structure is explored and the colony extinguishes. The Channeler Ant Model performance was successfully validated

on artificial images, without any parameter tuning when the image or the environment properties changed.

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