

Termites: a Retinex implementation based on a colony of agents

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ABSTRACT

This paper describes a novel implementation of the Retinex algorithm with the exploration of the image done by an ant swarm. In this case the purpose of the ant colony is not the optimization of some constraints but is an alternative way to explore the image content as diffused as possible, with the possibility of tuning the exploration parameters to the image content trying to better approach the Human Visual System behavior. For this reason, we used “termites”, instead of ants, to underline the idea of the eager exploration of the image. The paper presents the spatial characteristics of locality and discusses differences in path exploration with other Retinex implementations. Furthermore a psychophysical experiment has been carried out on eight images with 20 observers and results indicate that a termite swarm should investigate a particular region of an image to find the local reference white.

1. INTRODUCTION

During the past decades a great amount of research has been done on understanding human visual perception, which is not a trivial task as the Human Visual System (HVS) has complex and robust mechanisms to acquire useful informations from the environment. In particular, the color of an area is influenced by the chromatic content of the other areas of the scene. This psychophysiological phenomenon is referred as locality of color perception.

Lately different image processing methods and frameworks attempted to deal with locality of perception and to exhibit behaviors similar to HVS, such as iCAM and its evolutions,^{1–3} ACE⁴ and the various Retinex implementations, which are the interest of this work.

In the original Retinex, proposed by Land and McCann in 1971^{5,6} the locality of perception is achieved by long paths scanning across the image. The scientific community has continued to be interested in this model and its various applications, as reported in.^{7,8} Different implementations and analysis followed after this first work. These can be divided into two major groups, which differ in the way they achieve locality.

The first group explores the image using paths or extracting random pixels around the pixel of interest.^{9–11} The second group computes values over the image with convolution mask or weighting distances.^{12–14} Recent implementations, constructed to investigate the effects of different spatial samplings, replaces paths with random sprays, i.e. two-dimensional point distributions across the image, hence the name ”Random Spray Retinex” (RSR).¹⁵ In a follow-up, Kolås et al.¹⁶ developed the ”Spatio-Temporal Retinex-like Envelope with Stochastic Sampling” (STRESS) framework, where the random sprays are used to calculate two envelope functions representing the local reference of lighter and darker points. All these algorithms need an high density of samples in order to lower the amount of noise but they never sample the whole image in order to keep the local effect. Furthermore the number of sampling points needed increases drastically when increasing the image size and consequently also the computational time.

In this work we start from the random path approach of the first group in particular the Brownian motions models.^{17,18} Here, the idea of the paths is implemented using an artificial model inspired from a biological process: the *Ant Colony System* (ACS) model proposed by Dorigo et al. in 1991¹⁹ for the *Travelling Salesman Problem*.

During the last decades the ACS has been extended to several other combinatorial optimization problems²⁰ and to several other fields, included image processing.^{21–29} The novelty in this paper is to encapsulate the ACS in the Retinex framework.

The rest of this paper will be organized as follows: Section 2 briefly recalls the ACS system, followed by our proposal in Section 3. Section 4 presents the method of evaluation and next the results are presented and discussed in Section 5. Finally, in section 6 conclusions are drawn.

2. ANT COLONY SYSTEM MODEL

The *Ant Colony System* (ACS) model proposed by Dorigo et al. in 1991^{19,30} is able to solve instances of the *Travelling Salesman Problem* (TSP), an NP-hard problem in combinatorial optimization and theoretical computer science, where given a list of cities and their pairwise distances, the task is to find a shortest possible tour that visits each city exactly once. Optimal results with short computational time are shown when cities are on a plane and a path (edge) exists between each pair of cities (i.e., the TSP graph is completely connected).

Three ideas from natural ant behavior are transferred to the artificial ant colony:

1. The preference for paths with a high pheromone level,
2. The higher rate of growth of the amount of pheromone on shorter paths,
3. The trail mediated communication among ants.

An artificial ant k in city r chooses the city s to move to among those which do not belong to its working memory M_k by applying the following probabilistic formula:¹⁹

$$p_k(r, s) = \begin{cases} \frac{(\tau_{r,s})^\alpha (\eta_{r,u})^\beta}{\sum_{u \notin M_k} (\tau_{r,u})^\alpha (\eta_{r,u})^\beta} & s \notin M_k \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where $\tau_{r,u}$ is the amount of pheromone trail on edge (r, u) , $\eta_{r,u}$ is a heuristic function called visibility, which is the inverse of the distance between cities r and u and, α and β are parameters that allow a user to control the importance of the trail versus the visibility.

3. TERMITE RETINEX

Before introducing our model, we recall the basic idea of Brownian Retinex,¹⁰ where Relative channel lightness (R) at a point i is the mean value of the relative channel lightnesses (r) computed along N random paths j to the point i (Figure 1):

$$R^i = \frac{\sum_{k=1}^N r_k^{i,j}}{N} \quad (2)$$

where

$$r_k^{i,j} = \prod_{x \in \text{path}} \delta \cdot \left(\frac{I_{x+1}}{I_x} \right) \quad (3)$$

where I is the lightness intensity of the pixel x and δ is the reset mechanism.

In order to create the so called *Termite Retinex* (TR), the ant colony system needs some modifications, which will consist in the following assumptions and constraints:

1. Pixels are considered cities: a termite can choose to move only on one of the 8 neighboring pixels (no jump).
2. The preference for a brighter pixel: the visibility η is substituted with the bilateral distance c defined below, that we will refer to *closeness*.

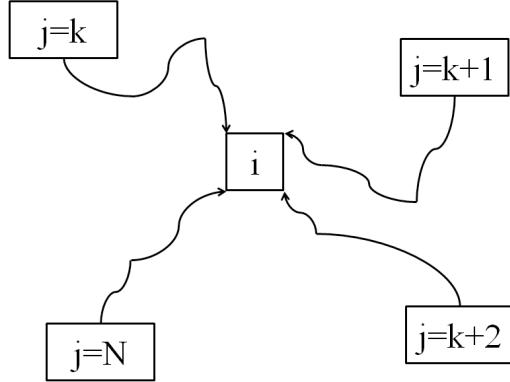


Figure 1. N random paths from j to the point i .

3. The preference for paths with a low *poison* level (we want divergence), in order to explore different areas of the image: the poison level is the inverse of the amount of pheromone: $\theta = \frac{1}{\tau}$.

So in our modified model an artificial termite k in pixel r chooses the pixel s to move to among those which do not belong to its working memory M_k by applying the following probabilistic formula:

$$p_k(r, s) = \begin{cases} \frac{(\theta_{r,s})^\alpha (c_{r,s})^\beta}{\sum_{u \notin M_k \text{ and } u \in N_8} (\theta_{r,u})^\alpha (c_{r,u})^\beta} & \text{if } s \notin M_k \text{ and } s \in N_8 \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where $\theta_{r,u}$ is the amount of poison on pixel u , $c_{r,u}$ is the bilateral distance between pixels r and u and, α and β are parameters which weight the importance of the poison versus the closeness, which is directly related to the brightness of the pixel. In case all the surrounding pixels have the same probability, one pixel is drawn randomly with uniform probability. The bilateral distance $c_{r,u}$ is defined as follows:

$$c_{r,u} = \frac{d_e + d_v}{\sqrt{2}} \quad (5a)$$

$$d_e = \sqrt{(x_r - x_u)^2 + (y_r - y_u)^2} \quad (5b)$$

$$d_m = |I(x_r, y_r) - I(x_u, y_u)| \quad (5c)$$

where I is the image channel and (x, y) are the coordinates of the pixels.

In daily life, termites are also known as “white ants” and as this model attempts an eager exploration in search of the reference local white, from that the name *Termite Retinex*.

4. METHODOLOGY OF EVALUATION

4.1 Choice of the Parameters

In the TSP problem, all the meta-heuristics attempt to find the optimal solution. In the field of spatial color algorithms,⁸ the optimal solution is not well defined and it is still subject to debate. For this reason, our purpose is confined to calculate a pleasant solution for the observer and several questions arise for the choice of the parameters:

1. How many termites k do we need to properly explore the image?
2. How far should a termite travel (number of pixels N_s indicating the length of the path)?

3. What values should α and β assume to make the termites explore the image properly?
4. How much poison θ should be add once a termite has visited a pixel in order to force divergence?

Answering the previous questions is not a trivial task and testing all the possible combinations of the parameters would be computational exhausting.

Pre-tests show that for a recalculation of each pixel a configuration with 250 termites ($k = 250$) visiting 1000 pixels ($N_s = 1000$) and a configuration with 500 termites ($k = 500$) visiting 500 pixels ($N_s = 500$) are adequate for our purpose of investigation and in particular the second combination has higher preference in a evaluation made by 10 observers on a set of three images. We underline to the reader that while the number of termites can be constant, the length of the path should be chosen according to the image size and in particular a termite should never touch all the points because we are interested in finding a local reference white and not the global white of the image.

In these preliminary studies the choices of α and β are directed as follows:

1. configuration A: $\alpha = 0.1$ and $\beta = 0.9$. In this case the poison θ has very low importance while the closeness c has very high importance. This causes a termite to easily choose a brighter pixel even if it has been previously visited by another termite.
2. configuration B: $\alpha = 0.9$ and $\beta = 0.1$. In this case the poison θ has very high importance while the closeness c has very low importance. This causes a termite to easily diverge from the path of another termite.
3. configuration C: $\alpha = 0.5$ and $\beta = 0.5$. In this case poison θ and closeness c have the same importance.

For the poison we have chosen to use the unit quantity $\theta = 1$.

4.2 Psychophysical Experiment

In order to evaluate which is the best configuration of the termites swarm, a psychophysical experiment has been carried out. A set of eight images chosen following the recommendations from^{31,32} were presented for comparison on neutral grey background to a total of 20 observers.

Three termited images with same parameters values $k = 500$ (number of termites) and $N_s = 500$ (number of visited pixels) but with the three different combinations of α and β described above were compared to its original and the observers were asked to choose one of the four images based on their preference. No limitation on time was given to the observers. All the participants were recruited from the computer science field with most of them having knowledge of image processing.

This experiment has been designed with the intent to investigate the importance of the poison in respect to the closeness.

5. RESULTS

Figure 2(a-p)-3(a-p) shows the eight original images on the left followed by the corresponding images processed by TR on the right for the three chosen configurations described above.

Figure 4 shows the preference of the 20 observers on the tested images for the first psychophysical experiment and we can clearly see that TR succeeds on all the images with all the three configurations, with respect to the original images.

Configuration A is preferred over B in all but one tied situation (Image 6), and A is also preferred over C in all but one (Image 6). Configuration C is preferred over B in all the eight images.

It is interesting to notice that configuration A produces slightly less contrasted images in respect to the two other configurations and this can be easily verified using some of the state-of-the-art contras measures.^{33,34}

A sign test at 99 % confidence interval confirms that all the three configurations are significantly better then the original and that TR configuration A is significantly different than TR configuration B.

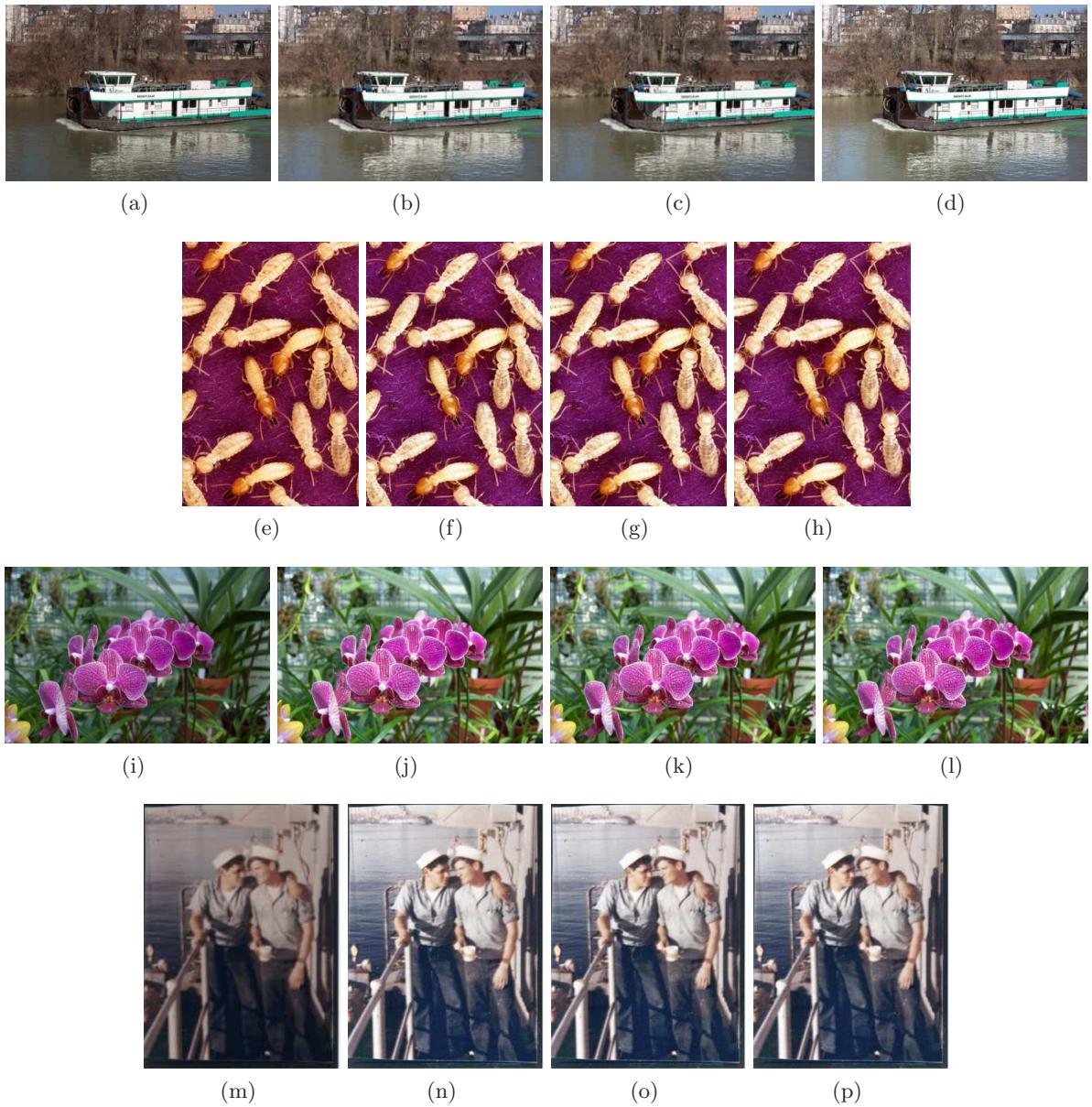


Figure 2. Original on the left followed by TR configuration A, B and C respectively.

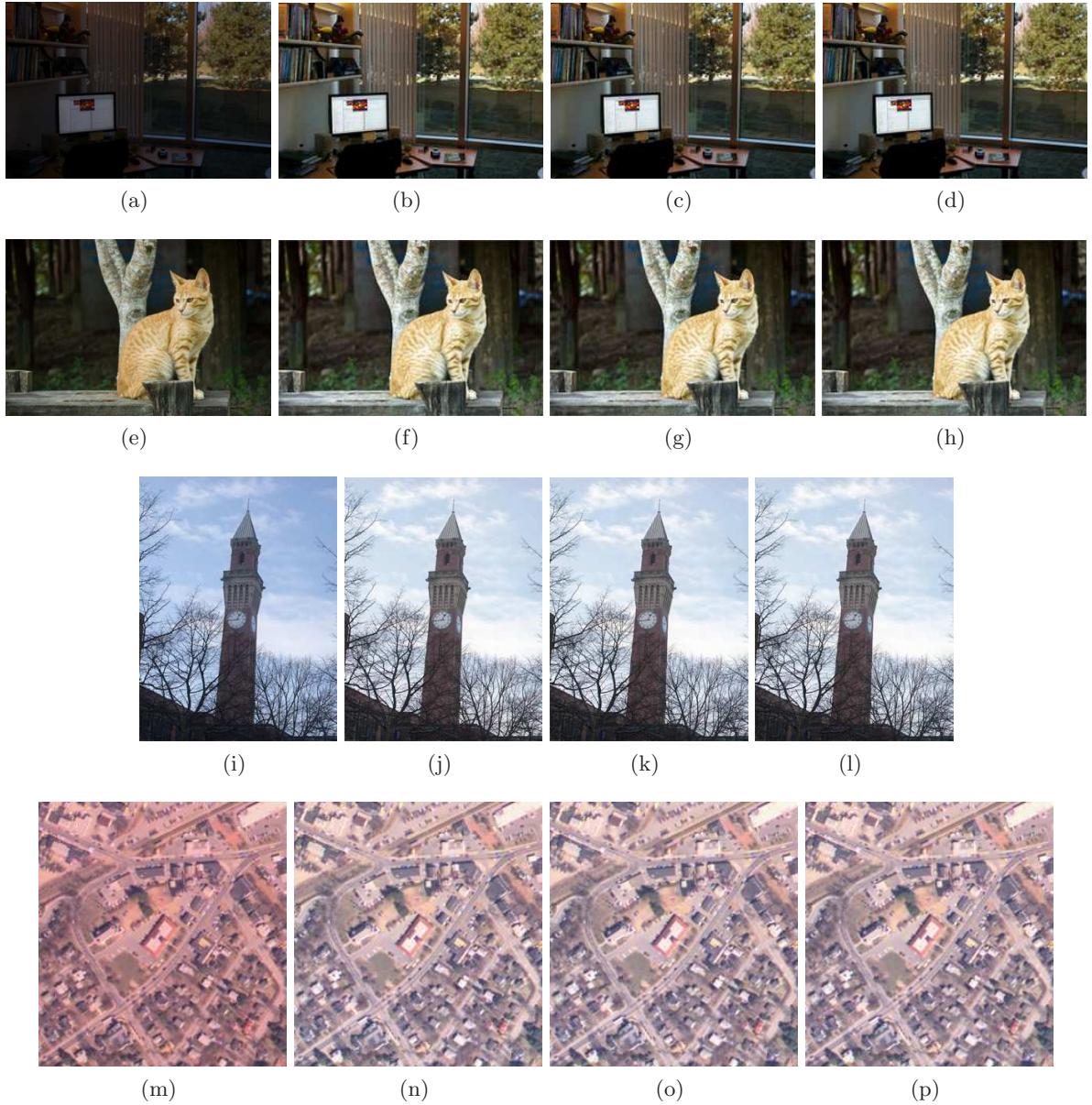


Figure 3. Original on the left followed by TR configuration A, B and C respectively.

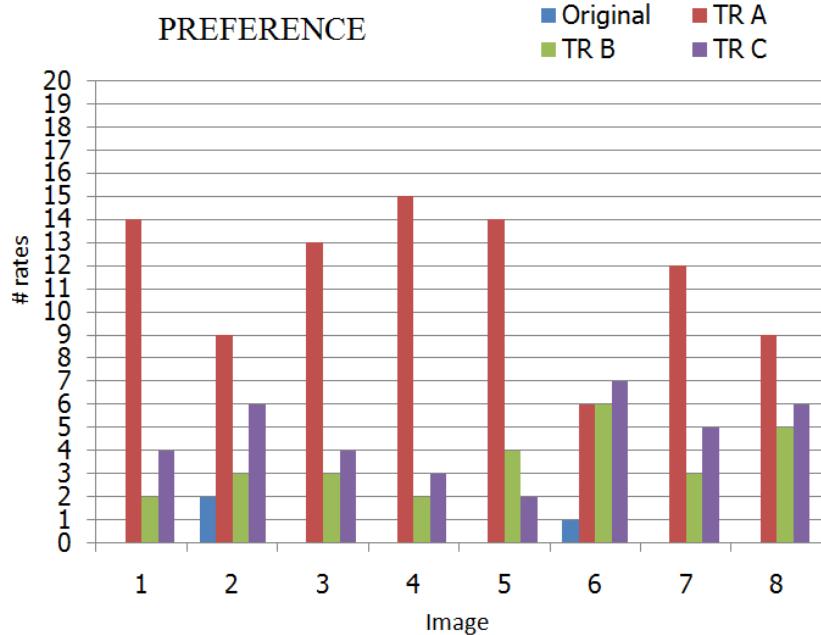


Figure 4. Observer's preference of TR with respect to its original on the 10 tested images for all the three configurations.

We remind the reader that configuration A ($\alpha = 0.1$ and $\beta = 0.9$) means that the poison θ has very low importance while the closeness c has very high importance and this causes a termite to easily choose a brighter pixel even if it has been previously visited by another termite. These results indicate that a termite swarm should investigate a particular region of an image to find the local reference white. Figure 5 show this different and particular behavior of TR with respect to traditional Brownian motion and the Pseudo-Brownian motion proposed by Montagna and Finlayson.¹⁸

6. CONCLUSIONS

We have developed a novel version of Retinex, implementing random paths using a modified version of the *Ant Colony System* (ACS) model proposed by Dorigo et al. in 1991.¹⁹ This new algorithm has been named *Termite Retinex* (TR) since the purpose is not the optimization of some constraints but an eager exploration of the image content, tuned in particular by two parameters, α and β which weight the relative importance of the so called “poison” and of the so called “closeness”.

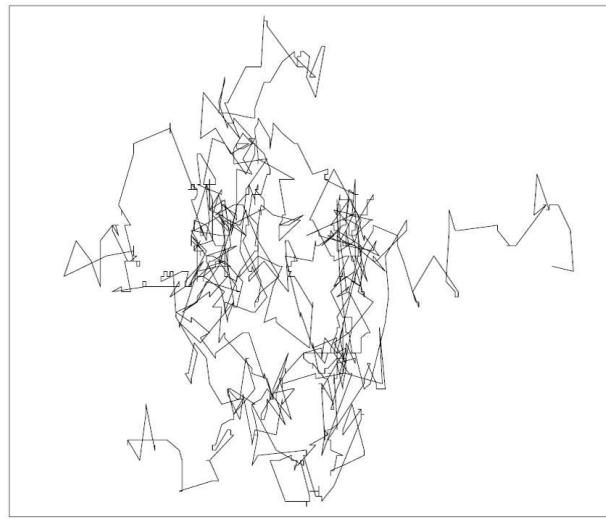
A psychophysical experiment has been carried out on eight images with 20 observers for three different configurations of α and β . Results confirm the efficacy of Termite Retinex on the tested images in comparison to the original. Regarding parameters, results has shown that giving very low importance to the poison and very high importance to the closeness causes a single termite to easily choose a brighter pixel even if it has been previously visited by another termite. These results indicate also that a termite swarm should investigate a particular region of an image to find the local reference white. A sign test at 95 % confidence interval confirms this investigation hypothesis.

7. ACKNOWLEDGMENT

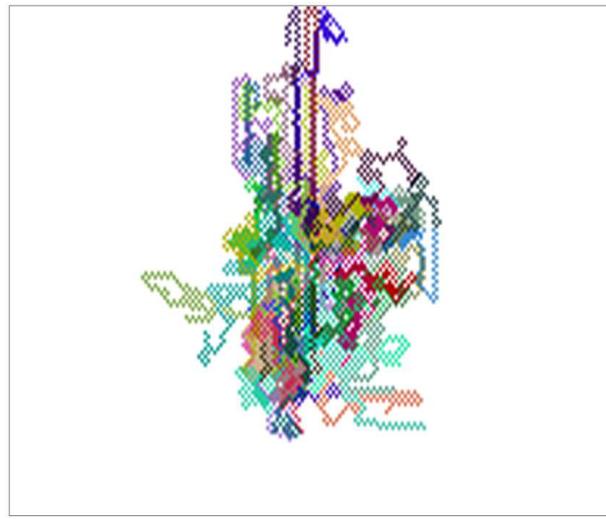
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(a)



(b)



(c)

Figure 5. Traditional Brownian motion investigation on the top, Pseudo-Brownian motion investigation proposed by Montagna and Finlayson,¹⁸ Termite investigation on the bottom. Figures 5(a)-5(b) have been extracted with courtesy from.¹⁸

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