Termite Retinex: A Novel Implementation based on a Colony of Agents

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Abstract

The Retinex algorithm originally presented by Land and McCann uses random paths to explore the image. Throughout the decades, many versions of the Retinex algorithm have been proposed, mainly differing in the way they explore the image, with e.g. random paths, random samples, convolution masks, and variational formulations. In this paper, we propose a step back towards the origin, replacing random paths by traces of specialized ants swarm, here called termites. In presenting the spatial characteristics of the proposed method we discuss differences in path exploration with other Retinex implementations. Two experiments on nine images with 20 observers have been carried out and the results indicate an higher preference of our proposal with respect to the original ones and a previous implementation of Retinex.

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 appearance 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.

Different image processing methods and frameworks attempted to deal with locality of image appearance and to exhibit behaviors similar to HVS, such as ACE [30], iCAM [10], and the various Retinex implementations, which are the interest of this work.

In the original Retinex, proposed by Land and McCann [20, 21] the locality of perception is achieved by long paths scanning across the image, accounting for pixel ratio computation in each chromatic channel. The scientific community has continued to be interested in this model and its various applications, as reported in [24, 23]. Different implementations and analysis followed after this first work and these can be divided into three 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 or computing ratio with neighbors in a multilevel framework [12, 22, 29, 13] while the second group instead computes values over the image with convolution masks or weighting distances [17, 1]. The third group, recently born, uses differential mathematical techniques based on Poisson-equation-type and variational approaches [18, 26].

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) [28]. In a follow-up, Kolås et al. [19] 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 [22, 25]. 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 1991 [8] for the *Travelling Salesman Problem*.

Inspired by the behavior of the ants in food foraging, Dorigo et al. developed in 1991 the so called *Ant Colony System* (ACS) for solving the well-known *Travelling Salesman Problem* (TSP) [8, 5], followed by some improvements [7]. Since its development and especially after the pioneer work *The Ant Colony Optimization Meta-Heuristic* (ACO) [6], more than hundreds of papers on ACO can be found in literature, several for solving other combinatorial optimization problems and some for extension to other fields [11, 3]. For an extensive and detailed description of ACO and its application in combinatorial optimization problems, we address the reader to Dorigo and Stützle book [9].

ACO has touched also the field of image processing,i.e. segmentation [2], classification [33], and edge detection [16] showing particular robustness against noise.

In this work we propose a new implementation of Retinex, following the first group approach, in particular substituting the Brownian paths with ant colony investigation of the image. 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 [8, 5] is able to converge to the optimal solution of 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 [8]:

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

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 also the basic idea of Brownian Retinex [22], where Relative channel lightness (L) at a point i is the mean value of the relative channel lightnesses (l) computed along N random paths from point j to the point i (Figure 1):

$$L^i = \frac{\sum_{h=1}^{N} l_h^{i,j}}{N} \tag{2}$$

where

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

where I is the lightness intensity of the pixel x, h is indicating the path and δ represents the reset mechanism as described in detail in [23].

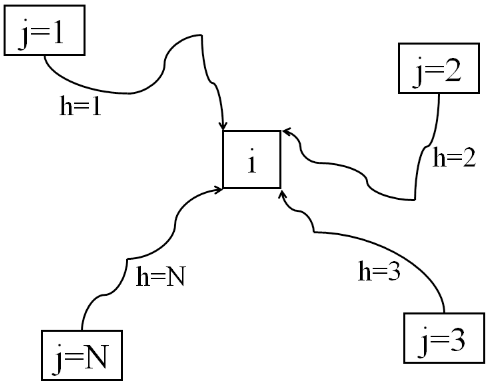

Figure 1: N random paths from point j to the point i.

Here we propose an implementation of Retinex following the mechanisms described above but with the novelty of replacing the Brownian paths with an ant colony investigation. Thus in order to create the so called *Termite Retinex* (TR), the ant colony system needs some modifications, which consists 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 jumps).

2. Preference for a brighter pixel: the visibility η is substituted with the bilateral distance c defined below, that we will refer to *closeness*.

3. 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:

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

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. M_k list contains the pixels that have already been visited by the k_{th} ant. The bilateral distance $c_{r,u}$ is defined as follows:

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

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

$$d_v = |I(x_r, y_r) - I(x_u, y_u)| \tag{5c}$$

where d_e and d_v are the distance in coordinates and in intensity values respectively, 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 Algorithm Characteristics

4.1 Tuning of the Parameters

In the TSP problem, all the meta-heuristics attempt to find the optimal solution. In the field of spatial color algorithms (SCA) [31, 23], the optimal solution depends on the task of the algorithm and it is still subject of research. In the work that we are presenting the goal of the filtering is a qualitative emulation of the HVS for an unsupervised image enhancement. Thus 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. Which values should α and β assume to make the termites explore the image properly?
4. How much poison θ should be added once a termite has visited a pixel in order to enforce the divergence of the paths?

Previous studies of investigation of the parameters [32] and indicate that for the recalculation of each pixel a particular configuration with 500 termites ($k = 500$) visiting 500 pixels ($N_s = 500$) with $\alpha = 0.1$ and $\beta = 0.9$ are in line with observers preference. This configuration comes out from a set of pre-tests and an experiment with eight images and 20 observers designed with the intent to investigate the importance of the poison in respect to the closeness and as consequence how to direct the termite swarm [32]. Results have shown a higher observer preference for low values of α and high values of β. We emphasize the fact that setting $\alpha = 0.1$ 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, resulting in this way in milder changes of the original overall contrast. 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. For the poison we have chosen to use the unit quantity $\theta = 1$ and leave the enforce of the divergence of paths for future work.

4.2 Computational Complexity

The computational complexity of the *Ant Colony System* proposed in 1991 [8] is $O(NC \cdot n^3)$, where NC is the number of ant cycles and n is the number of cities in a istance of the TSP problem. Although its higher computational complexity the ACS reaches the optimal solution of the TSP problem in a shorter computational time than other heuristics [14]. In our case the ant cycle is not necessary because we do not need to converge to an optimal solution and furthermore at each pixel recomputation each termite does not have to touch all the pixels. As consequence the computational complexity of the *Termite Retinex* is given by:

$$O(k \cdot N_s \cdot n) \tag{6}$$

where k is the number termites, N_s is the number of pixel (length of the path) visited by a termite and n in this case is the number of pixels in the image. The TR follows the same computational complexity of other SCAs, such as RSR or STRESS which have a computational complexity of $O(N \cdot M \cdot n)$, where N is the number of iterations, M is the number of samples and n is the number of pixels in the image. On the other hand regarding the computational time of TR, implemented in Matlab with no optimization, can be slower than other SCAs which have been optimized i.e. in CUDA.

5 Test Results and Discussion

In order to evaluate the quality of the TR, two experiments with users have been carried out. A set of nine images, shown in Figure 2, chosen following the recommendations from [15, 4], were evaluated in a pairwise comparison on neutral grey background by a total of 20 observers, recruited from the computer science field with most of them having knowledge of image processing.

In the first experiment each image processed with TR was compared to its original while in the second experiment each image was compared to the one processed with RSR. Both experiments were performed in uncontrolled environments as suggested from Zuffi et al. [34] and observers were asked to choose the image based on their overall preference; no indication of any image quality attribute were given to the partecipants [27]. While the first experiment has been designed with the intent of evaluating the efficacy of the method the second experiment has been designed with the purpose evaluating the reconsidered path-based approach of TR against a most recent spray-based one such as RSR.

Figure 3 shows the preference of the 20 observers on the tested images for the experiment and we can clearly see that TR succeeds on all the images with three of them with a preference equal to 100%. A sign-test at 95% confident interval shows that TR is significantly better than the original.

Figure 4 shows the overall preference of the 20 observers for the second experiment, where TR was compared to RSR. TR is preferred for all the nine tested images, except for a draw with Image 5. Only Image 4 has a noticeable preference of 100%. A sign-test at 95% confidence interval shows that TR is significantly better than RSR.

Examples of images processed with RSR with respect to TR are shown in Figure 5. In order to lower as much as possible the amount of noise, all the images were processed with RSR using 1000 iterations ($N = 1000$) and 4000 samples ($M = 4000$), which require longer computational time with respect to TR, using the same implementation language and no optimization techniques. For further details we refer to the reader to Section and to [28, 19].

Since Retinex is a white patch algorithm[23], TR follows the same behavior. The brightest color in the image is mapped to white and this is performed locally, in a way that is edge preserving. Furthermore like other SCAs[31], TR performs a content driven histogram flattening. As consequence TR is able to perform color correction as shown in Figure 6, where the red component is balanced, and dynamic enhancement as shown in Figure 7, where the overall visibilty is recovered.

(a) Image 1

(b) Image 2

(c) Image 3

(d) Image 4

(e) Image 5

(f) Image 6

(g) Image 7

(h) Image 8

(i) Image 9

Figure 2: The nine original images chosen for the two experiments.

In conclusion we can candidate TR as new path-based Retinex with the particular novelty of swarm intelligence behavior, which yields in several advantages with respect to spray-based approaches, which have leaded lately.

6 Conclusion

We have developed a novel implementation of Retinex, reconsidering the idea of the paths and taking an existing artificial model inspired from a biological process. This new algorithm named *Termite Retinex* (TR) has marveled from the modification of the *Ant Colony System* (ACS) model proposed by Dorigo et al. in 1991 [8]. In this case the purpose of TR 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 importance of the so called “poison” and of the so called “closeness”. Following suggestions from

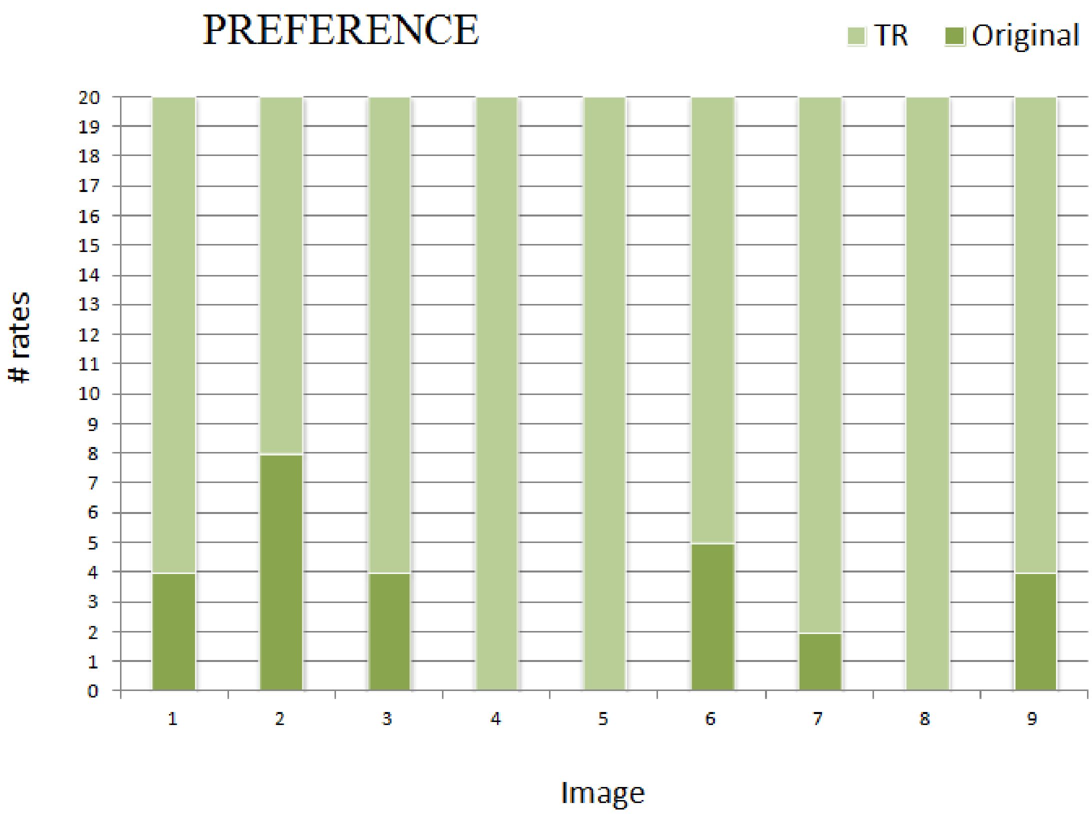

Figure 3: First experiment results: observers preference of TR with respect to its original on the nine tested images.

previous studies, indicating that giving very low importance to the poison an very high importance to the closeness which causes a termite swarm investigating a particular region of an image to find the local reference white, we have carried out two experiments in order to evaluate the quality of TR. A set of nine images processed with TR were evaluated by 20 observers, first in comparison with the original and then with a previously developed implementation of Retinex. Results confirm the efficacy of the method with higher observers preference in both experiments and a sign-test at 95% confident interval confirms this statement.

Future works will focus on different open issues: extending TR to color gamut mapping and color-to-grey, automatic retrieval of the parameters α and β and the length of the path based on the image content.

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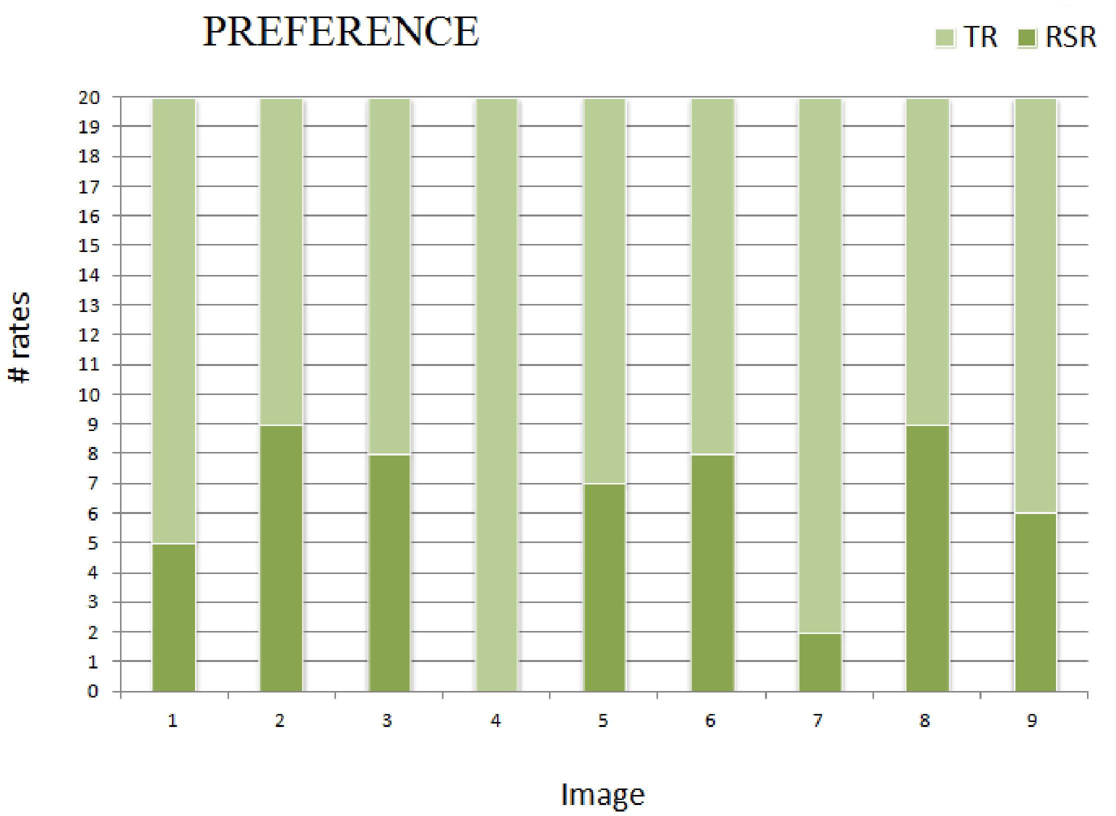

Figure 4: Second experiment results: observers overall preference of TR with respect to RSR on the nine tested images.

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(a)

(b)

Figure 5: Image 4 and Image 9 processed by RSR on the left and processed by TR on the right.

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Figure 6: Unsupervised color correction of Image 8.

Figure 7: Unsupervised dynamic range stretching of Image 5.

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