# Visual saliency detection in image using ant colony optimisation and local phase coherence

L. Ma, J. Tian and W. Yu

A new visual saliency detection approach is proposed. The proposed approach exploits the ant colony optimisation technique to measure the image's saliency via depositing the pheromone (through ants' movements) on the image. Furthermore, the ants' movements are steered by the local phase coherence of the image. Experimental results are presented to demonstrate the performance of the proposed approach.

*Introduction:* Visual saliency detection has been of great research interest in recent years, since it has potential for a wide range of applications, such as object detection and content-based image retrieval. The existing approaches can be classified into two categories: bottom-up and top-down. The former is an image-driven approach to select visual information based on the saliency in the image itself, while the latter is a goal-driven approach based on a user-defined task. This Letter focuses on the bottom-up approaches.

Itti *et al.* [1] introduced a biologically-inspired saliency model. They proposed to use a set of feature maps from three complementary channels as intensity, colour, and orientation. The normalised feature maps from each channel were then sent into a 'Winner-take-all' competition to select the most conspicuous image locations as the overall saliency map. Ma and Zhang [2] proposed a local contrast-based saliency model, which is obtained from summing differences of image pixels with their respective surrounding pixels in a small neighbourhood. A fuzzy-growing method then segments salient regions from the saliency map. Wu *et al.* [3] proposed to determine the saliency map using low-level features, including luminance, colour and region information, then thresholding these feature maps using a just noticeable difference (JND) model and integrating them into a final saliency map.

The two major challenges in visual saliency detection are: (i) the mechanism of saliency measure, and (ii) image features extracted. To tackle the first challenge, a novel approach is proposed in this Letter to exploit the ant colony optimisation (ACO) [4] technique to establish a pheromone matrix that represents the saliency presented at each pixel position of the image. The pheromone matrix is estimated via the movements of a number of ants, which are dispatched to move on the image. More specifically, the positions, where more ants visit, will yield more pheromone. This is inspired by the natural collective foraging behaviour of ant species that ants can deposit pheromone on the ground in order to mark some favourable path that should be followed by other members of the colony. It is important to note that, although the ACO technique has already been successfully applied to a few image processing tasks [5–8] (e.g. image segmentation and classification, denoising), in this Letter it is the first time it has been exploited to perform image saliency detection. Secondly, the ants' movements need to be adaptive according to image features. For that, the proposed approach exploits the local phase coherence [9] of the image, which is able to provide a perceptual image representation that is fairly consistent with the human visual system. This has been supported by the physiological evidence that shows high human perception response to signal characteristics with high local phase coherence [9].

*Proposed algorithm:* The proposed approach aims to construct a pheromone matrix (denoted as $\boldsymbol{\tau}$) for the image; each entry of the matrix represents certain saliency at each pixel location of the image. The detailed procedure of the proposed approach is as follows.

- *Step 1*: The proposed approach starts from setting the initial value of each component of the pheromone matrix $\boldsymbol{\tau}^{(0)}$ to be a constant $\boldsymbol{\tau}_{init}$. Furthermore, one ant is assigned to each pixel position (called node) of the image.
- *Step 2*: Each ant will consecutively move on the image for $L$ steps. This ant moves from the node $(l,m)$ to its neighbouring node $(i,j)$ according to a transition probability that is defined as

$$p^{(n)}_{(l,m),(i,j)} = \frac{(\tau^{(n-1)}_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum\limits_{(i,j)\in\Omega_{(l,m)}} (\tau^{(n-1)}_{i,j})^{\alpha}(\eta_{i,j})^{\beta}} \tag{1}$$

where $\tau^{(n-1)}_{i,j}$ is the pheromone value of the node $(i,j)$, $\Omega_{(l,m)}$ are the neighbourhood nodes of the node $(l,m)$, $\eta_{i,j}$ represents the heuristic information at the node $(i,j)$, the constants $\alpha$ and $\beta$ represent the influence of the pheromone matrix and the heuristic matrix, respectively. Furthermore, the permissible range of the ants' movement is proposed to be 8-connectivity neighbourhood. The heuristic information $\eta_{i,j}$ in (1) is determined by the local phase coherence [9] of the image, which is extracted using a log-Gabor filter bank. More specifically, the local phase coherence at the position $\boldsymbol{x}$ is formulated as

$$\eta(\boldsymbol{x}) = \frac{1}{2}\sum_{\theta}[(c(\boldsymbol{x},\theta)sin(\theta))^2 + (c(\boldsymbol{x},\theta)\cos(\theta))^2] + \frac{1}{2}\sqrt{4\left(\sum_{\theta}(c(\boldsymbol{x},\theta)\sin(\theta)c(\boldsymbol{x},\theta)\cos(\theta))\right)^2 + \left(\sum_{\theta}[(c(\boldsymbol{x},\theta)\cos(\theta))^2 - (c(\boldsymbol{x},\theta)\sin(\theta))^2]\right)^2} \tag{2}$$

where $c(\boldsymbol{x}, \theta)$ is the local phase coherence at orientation $\theta$ defined as
$c(\boldsymbol{x},\theta) = (\sum W(\boldsymbol{x},\theta)|A_n(\boldsymbol{x},\theta)\Delta\phi_n(\boldsymbol{x},\theta)|)/(\sum A_n(\boldsymbol{x},\theta) + \xi)$,
$\Delta\phi_n(\boldsymbol{x},\theta) \overset{n}{=} \cos(\phi_n(\boldsymbol{x},\theta) - \bar{\phi}(\boldsymbol{x},\theta)) - |\sin(\phi_n(\boldsymbol{x},\theta) - \bar{\phi}(\boldsymbol{x},\theta))|$,
$W$ represents the frequency spread weighting factor, $A_n$ and $\varphi_n$ represent the amplitude and phase at wavelet scale $n$, respectively, $\bar{\varphi}_n$ represents the weighted mean phase, and $\xi$ is a small constant used to avoid the division by zero. All the above-mentioned parameters are the same as those used in [9].

- *Step 3*: The pheromone content of the coefficient on the ant's path is updated. First, after the movement of each ant, each component of the pheromone matrix is updated according to

$$\tau^{(n-1)}_{i,j} = \begin{cases} (1-\rho)\times\tau^{(n-1)}_{i,j} + \rho\times\Delta^{(k)}_{i,j}, & \text{if}\,(i,j)\,\text{is visted by the current}\ k\text{th ant} \\ \tau^{(n-1)}_{i,j}, & \text{otherwise} \end{cases} \tag{3}$$

where $\rho$ controls the degree of the updating of $\tau^{(n-1)}_{i,j}$, and $\Delta^{(k)}_{i,j}$ is determined by the heuristic matrix, i.e. $\Delta^{(k)}_{i,j} = 1/\eta_{i,j}$. Secondly, after the movement of all ants, the pheromone matrix is updated as

$$\tau^{(n)} = (1-\phi)\tau^{(n-1)} + \phi\tau^{(0)} \tag{4}$$

where ϕ is the pheromone decay coefficient. Steps 2 and 3 are iteratively run for $N$ iterations. Finally, the pheromone matrix $\boldsymbol{\tau}^{(n)}$ can be obtained to represent the saliency of the image.

*Experimental results:* Experiments were conducted to demonstrate the performance of the proposed approach. Test images were obtained from the MSRA Salient Object Database [10]. The parameters of the proposed approach were experimentally set as follows: $\tau_{init} = 0.001$, $\alpha = 1$, $\beta = 2$, $L = 15$, $\rho = 0.1$, and $\phi = 0.3$. The Gabor filter used for computing the local phase coherence was implemented using three scales and four orientations.

The first experiment was to compare the saliency map produced by the proposed approach with those of [11–14]. The above-mentioned four approaches were implemented using their respective programs provided by authors online. Owing to the limited space of this Letter, only saliency maps obtained using one test image are presented in Fig. 1, where the white pixels represent the positions with more important visual saliency. As seen from Fig. 1, the proposed approach is fairly consistent to the human visual system owing to two key components of the proposed approach. First, the proposed approach exploits the local phase coherence of the image to measure the degree of the saliency of the image. This is able to provide a perceptual image representation that is fairly consistent to the human visual system and has been justified in the physiological evidence [9]. Secondly, the proposed approach exploits the ACO technique to exploit both local information (through the ants' movements) and global information (through the ants' collective behaviour) of the image to measure the significance of saliency at each pixel position. This is in contrast to conventional approaches which only use local information of the image. Consequently, there is no broken line or isolated pixels in the saliency map obtained by the proposed approach.

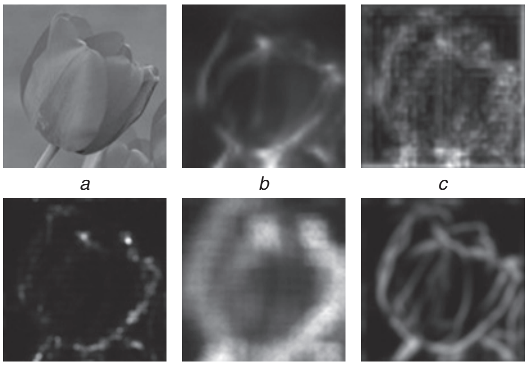


**Fig. 1** *Various visual saliency maps*

(*a*) Test image Flower
(*b*)–(*e*) References [11–14], respectively
(*f*) Proposed approach

The second experiment was to explore the computational complexity (in terms of the run time) of the proposed approach. The above approaches were implemented using the Matlab programming language and run on a PC with an Intel Core2 1.67 GHz CPU and a 4096 MB RAM. As seen from Table 1, the computational complexity of the proposed approach is fairly large compared with that of the other four approaches. This is because the proposed approach needs to iteratively exploit the ants' movements to calculate the pheromone matrix.

**Table 1:** Run-time comparison (in seconds)

| Test image | [11] | [12] | [13] | [14] | Proposed approach |
|---|---|---|---|---|---|
| Board | 11.81 | 6.72 | 0.83 | 28.94 | 26.39 |
| Flower | 5.44 | 0.89 | 0.23 | 1.89 | 7.53 |

*Conclusions:* A novel approach is proposed to perform visual saliency detection with attractive performance. The proposed approach exploits the local phase coherence of the image to guide the movement of a set of ants, which deposit the pheromone on the image and enable measurement of the image's saliency. The proposed approach is able to produce a saliency map that is more consistent with the human visual system than a number of existing approaches [11–14], as verified in our experiments. There are several issues that need to be further investigated. The first issue is how to objectively evaluate the performance of visual saliency detection, since only subjective performance comparison is presented in this Letter. Secondly, only the monotone image data is considered in this Letter. To address the colour image, the saliency maps produced from different colour components need to be aggregated to a single map by considering the correlations among the colour components.

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