A Spatial Random-Meaningful Neighbourhood Topology in PSO for Edge Detection in Noisy Images

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ABSTRACT

The continuity of edges is very important in some image processing applications. The Canonical Particle Swarm Optimisation (CanPSO) has been used for the detection of continuous edges. The Fully Informed Particle Swarm (FIPS) is another well-known version of PSO with interesting features to overcome noise but it has never been used to detect edges in noisy images. In this paper, the performance of CanPSO and FIPS is investigated for detecting edges in noisy images when they utilise different topologies. A novel spatial random-meaningful topology is also developed and utilised within the PSO-based edge detection algorithm. Experimental results indicate that the localisation accuracy of the PSO-based edge detector with the novel topology is higher than other static and dynamic topologies in most cases.

Categories and Subject Descriptors

I.4 [**Image Processing and Computer Vision**]: Miscellaneous; G.1.6 [**Optimization**]: Constrained optimization

Keywords

Edge detection, particle swarm optimisation, PSO topologies

1. INTRODUCTION

The continuity of the edges recognised by an edge detector is very important in many image processing applications. Many algorithms have been proposed to detect edges in noisy images in different frameworks. Their performance generally decreases in noisy and illuminated images and most of them produce broken edges in such images.

In our previous work [5], we applied Particle Swarm Optimisation (PSO) to detect continuous edges in real grey level images corrupted by Gaussian and impulsive noise through developing a novel optimisation criterion. We showed that the accuracy of the PSO-based algorithm was higher than the Canny edge detector as a Gaussian-based edge detector and the robust rank-order (RRO) detector as a statistical-based edge detector.

The Canonical PSO (CanPSO) [1] and the Fully Informed Particle Swarm (FIPS) [4] are two well-known versions of PSO with different features. Although FIPS has interesting features to overcome noise, only CanPSO has been used to detect edges in noisy images and the fully connected graph has been chosen as its neighbourhood structure. Bratton and Kennedy [1] used PSO for the optimisation of different functions from different areas and demonstrated that a complete experimentation is required to choose an ideal topology for a particular problem. Since the performance of static and dynamic topologies is different in various applications and in various versions of PSO [4], in this paper, we aim to investigate the performance of CanPSO and FIPS on the detection of edges in noisy images, compare their accuracy when they are equipped with different well-known static (fully connected, ring and toroidal topologies) and two dynamic topologies (gradually increasing directed neighbourhood (GIDN) [3] and random dynamic topology), and improve the performance of the PSO-based edge detector through developing a novel dynamic topology which uses spatial-meaningful information.

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2. BACKGROUND

FIPS [4] is a well-known version of PSO in which each particle is influenced by all of its neighbours specified by a neighbourhood topology, whereas in CanPSO, each particle shares information just with the best neighbour. Therefore, in FIPS there is a stronger swarm influence than CanPSO. Since the particles in FIPS are usually influenced by a more local neighbourhood than CanPSO, FIPS's population usually has higher diversity. Since each particle's velocity is influenced by the average between its neighbours' positions and its current position, we expect that FIPS can deal with noisy images better than CanPSO.

The topology is an important feature of PSO as it defines the neighbourhood structure among the particles and shows how they exchange information. The neighbourhood topology specifies the speed of information flow among particles. Since the exploration and exploitation abilities of the PSO algorithm can be controlled by adjusting the speed of information flow, the topology can be used as a mechanism to tune these abilities of the algorithm.

3. SPATIAL RANDOM-MEANINGFUL TOPOLOGY (SRMT) FOR A PSO-BASED EDGE DETECTOR

In the GIDN topology proposed in [3], the number of neighbours of each particle is gradually increased; new neighbours are randomly chosen from the particles which are not still connected to the particle and added to the particle's neighbourhood. In GIDN, the number of connections are gradually increased based on Equation (1) and these directed connections are randomly selected. The number of neighbours for particle P_i is calculated as:

$$|H_K(P_i)| = \left\lfloor \left(\frac{K}{MaxIter}\right)^{\alpha} \times N + \beta \right\rfloor \quad (1)$$

where N is the number of particles, $H_K(P_i)$ is the set of the neighbours of particle P_i at iteration K, $\lfloor . \rfloor$ is the floor function, $MaxIter$ is the maximum number of iterations, α is a parameter to control the speed of information flow through increasing the neighbourhood size, and β is the initial neighbourhood size at the first iteration ($K = 0$). In this model, each particle starts with β neighbours and randomly adds $|H_K(P_i)| - |H_{K-1}(P_i)|$ particles to its neighbourhood without taking their spatial information into account. There are several versions of PSO that utilise spatial information to update the velocity and position of the particles. In SRMT, we aim to use spatial-meaningful information in order to more effectively select the neighbours of each particle at a random way. To meaningfully choose the neighbours of a particle (P), we first assign a neighbourhood probability to each particle (P_n) in the PSO population at iteration K. We then select $|H_K(P)| - |H_{K-1}(P)|$ distinct particles which still do not have any connection with P and add them to its neighbourhood. Since the closest particles to a particle are expected to have a higher probability to be a neighbour of the particle, we define this probability as:

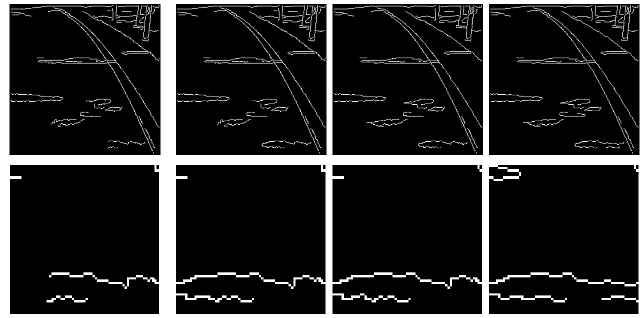
$$Prob_K(P_n\, is\, a\, neighbour\, of\, P) = 1 - \frac{Dist_K(P, P_n)}{\sum_{P_i \notin H_{K-1}(P)} Dist_K(P, P_i)} \quad (2)$$

where $Dist_K(P, P_i)$ is the distance between particles P and P_i in fitness space at iteration K. So, $Dist_K(P, P_i) = |Fitness(P) - Fitness(P_i)|$. In Equation (2), if particle P_n is closer to P in the fitness space, its probability of being a neighbour of particle P is higher and if their distance is larger, the probability is lower.

4. RESULTS AND DISCUSSION

To compare the performance of CanPSO and FIPS with different topologies and validate the performance of the novel topology (SRMT), we apply these algorithms on a set of benchmark images from [2].

Our experiments showed that CanPSO with the ring topology (RT) can work better than CanPSO with the fully connected graph (FCG) and the toroidal (TRO) topologies in 92.5% of the cases. Unlike CanPSO whose accuracy becomes higher when the ring topology is chosen, the accuracy of FIPS is higher in 98.7% of the cases when TRO is chosen as a neighbourhood structure. FIPS with TRO increases the accuracy over FIPS-RT and FIPS-FCG by approximatly 1.8% and 3.9% on average respectively. The comparison of FIPS-SRMT with other dynamic topologies showed that FIPS-SRMT is statistically better or equal in 83.5% of the cases. The accuracy of FIPS-SRMT is statistically the same as FIPS-GIDN in 38 cases out of 40 while CanPSO-SRMT is the same as CanPSO-GIDN in 13 cases and is better in 26 cases. This implies that SRMT can work better within CanPSO than FIPS. The dynamic topologies can be approximately ranked as {FIPS-SRMT, FIPS-GIDN}, CanPSO-SRMT, CanPSO-GIDN, CanPSO-Random, FIPS-Random from highest to lowest accuracy. FIPS with SRMT increases the accuracy over FIPS-GIDN, FIPS-Random, CanPSO-SRMT, CanPSO-GIDN, CanPSORandom by approximatly 1%, 1.3%, 1%, 1.5% and 1.2% on average respectively. FIPS-SRMT also performs better than CanPSO-RT and FIPS-TRO and its accuracy is statistically better or equal to CanPSO-RT in 75% of the cases and that of FIPS-SRMT is higher or equal with FIPS-TRO in 100% of the cases. Our comparison also showed that the novel dynamic topology increases the accuracy by 7.4% on average over CanPSO-FCG and by 1.5% over CanPSO-GIDN.



CanPSO-FCG [5] FIPS-TRO FIPS-GIDN FIPS-SRMT

Figure 1: The resulting images from applying CapPSO-FCG, FIPS-TRO, FIPS-GIDN and FIPS-SRMT.

Figure 1 shows some images resulting from CanPSO with FCG and FIPS with TRO, GIDN and SRMT. The second row shows an enlarged version of a small region of the resulting images in the first row. For the street image, CanPSO-RT does not work well on the areas in shadow on the road; the dynamic topologies perform better. These areas are very cluttered. FIPS-SRMT can deal with the detection of edges in such areas better than the other two dynamic topologies (see the bottom of enlarged versions for the street image and the edges in the areas in shadow).

5. CONCLUSIONS

In this paper, different static and dynamic topologies were implemented in CanPSO and FIPS, and were applied within a PSO-based edge detection algorithm. Our experiments showed that CanPSO performs better when it uses the ring topology. Unlike CanPSO, FIPS with TRO has a higher accuracy than the other static topologies. We also developed a novel dynamic topology which uses spatial meaningful information in order to compute the neighbourhood probability of each particle to be a neighbour of another particle. We used this probability to randomly choose the neighbours of each particle at each iteration. Our experiments showed that using SRMT improves the accuracy of the two versions of PSO-based edge detection algorithms in comparison to other topologies.

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