A Modified Differential Evolution for Autonomous Deployment and Localization of Sensor Nodes

Subhrajit Roy
Jadavpur University
Kolkata 700032, India

Sk. Minhazul Islam
Jadavpur University
Kolkata 700032, India

Saurav Ghosh
Jadavpur University
Kolkata 700032, India

Swagatam Das
Jadavpur University
Kolkata 700032, India
swagatamdas19@yahoo.co.in

Ajith Abraham
VŠB - Technical University of Ostrava
Ostrava, Czech Republic
ajith.abraham@ieee.org

Pavel Krömer
VŠB - Technical University of Ostrava
Ostrava, Czech Republic
pavel.kromer@vsb.cz

ABSTRACT
The performance of a wireless sensor network (WSN) is largely influenced by the optimal deployment and accurate localization of sensor nodes. This article considers real-time autonomous deployment of sensor nodes from an unmanned aerial vehicle (UAV). This kind of deployment has importance, particularly in *ad hoc* WSNs, for emergency applications, such as disaster monitoring and battlefield surveillance. The objective is to deploy the nodes only in the terrains of interest, which are identified by segmentation of the images captured by a camera on board the UAV. In this article we propose an improved variant of an important evolutionary algorithm Differential Evolution for image segmentation and for distributed localization of the deployed nodes. Simulation results show that the proposed algorithm ADE_*p*BX performs image segmentation faster than both types of algorithm for optimal thresholds. Moreover in case of localization it gives more accurate results than the compared algorithms.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search --- *Heuristic methods*; G.1.6 [**Numerical Analysis**]: Optimization --- *Global optimization*; G.3 --- *Probabilistic algorithms*

General Terms
Algorithms, theory, experimentation

Keywords
Differential Evolution, Wireless Sensor Network, Image Thresholding, Node Localization**.**

1. INTRODUCTION
In this paper, an improved Differential Evolution (DE) [1] variant, ADE_*p*BX is proposed and applied to an interesting application-autonomous deployment by image thresholding [2] and localization [3] of sensor nodes. ADE_*p*BX has successfully performed 2-level, 3-level and 4-level thresholding of an image captured from a downward-pointing camera on board the UAV and also faster than the other competitor algorithms. ADE_*p*BX has also outperformed other algorithms for post deployment distributed node localization in the WSN.

GECCO'11, July 12–16, 2011, Dublin, Ireland.
ACM 978-1-4503-0690-4/11/07.

2. THE ADE_*p*BX ALGORITHM
In DE, greedy strategies like DE/current-to-best/*k* and DE/best/*k* benefit from their fast convergence by guiding the evolutionary search with the best solution so far discovered, thereby converging faster to that point but in such cases due to exploitative tendencies the particle may get trapped into local optima. Taking into consideration these facts and to overcome the limitations of fast but less reliable convergence performance of DE/current-to-best/1 scheme, in this article, we propose a less greedy and more explorative variant of the DE/current-to-best/1 mutation strategy by utilizing the best vector of a dynamic group of *q*% of the randomly selected population members for each target vector. The new scheme, which we call DE/current-to-gr_best/1, can be expressed as:

$$\vec{V}_{i,G} = \vec{X}_{i,G} + F \cdot (\vec{X}_{gr\_best,G} - \vec{X}_{i,G} + \vec{X}_{r_1^i,G} - \vec{X}_{r_2^i,G}$$

where $\vec{X}_{gr\_best,G}$ is the best of *q*% vectors randomly chosen from the current population whereas $\vec{X}_{r_1^i,G}$ and $\vec{X}_{r_2^i,G}$ are two distinct vectors picked up randomly from the current population. The parameter q is known as the group size which controls the greediness of the mutation scheme DE/target-to-gr_best/1. The crossover operation used in ADE_*p*BX is named as *p*-best crossover where for each donor vector, a vector is randomly selected from the *p* top-ranking vectors (according to their objective function values) in the current population and then normal binomial crossover between the donor vector and the randomly selected *p*-best vector to generate the trial vector at the same index.

2.1. Parameter Adaptation Schemes in ADE_*p*BX

2.1.1. *Scale Factor Adaptation*
At every generation, the scale factor F_i of each individual target vector is independently generated as:

$$F_i = Cauchy(F_m, 0.1)$$

where $Cauchy(F_m, 0.1)$ is a random number sampled from a Cauchy distribution with location parameter F_m and scale parameter 0.1. Denote $F_{success}$ as the set of the successful scale factors, so far, of the current generation generating better trial vectors that are likely to advance to the next generation. Also let $mean_A(F_{G-1})$ is the simple arithmetic mean of all scale factors associated with population members in generation $G-1$.

Location parameter F_m is updated at the end of each generation in the following manner:

$$F_m = w_f \cdot F_m + (1 - w_f) \cdot mean_{Pow}(F_{success}) \quad (1)$$

The weight factor w_f is set in the following way:

$$w_f = 0.9 + 0.01 \cdot rand(0,1) \quad (2)$$

where $mean_{Pow}$ stands for power mean given by:

$$mean_{Pow}(F_{success}) = \sum_{x \in F_{success}} (x^n / |F_{success}|)^{1/n} \quad (3)$$

2.1.2. Crossover Probability Adaptation

At every generation the crossover probability Cr_i of each individual vector is independently generated as:

$$Cr_i = Gaussian(Cr_m, 0.1) \quad (4)$$

where $Gaussian(Cr_m, 0.1)$ is a random number sampled from a Gaussian distribution according with mean Cr_m and standard deviation 0.1. Cr_i is regenerated if it falls outside the interval [0, 1]. Denote $Cr_{success}$ as the set of all successful crossover probabilities Cr_i 's at the current generation. The mean of the normal distribution Cr_m updated at the end of each generation as:

$$Cr_m = w_{Cr} \cdot Cr_m + (1 - w_{Cr}) \cdot mean_{Pow}(Cr_{success}) \quad (5)$$

with the weight being set as:

$$w_{Cr} = 0.9 + 0.001 \cdot rand(0,1) \quad (6)$$

The power mean is calculated as:

$$mean_{Pow}(Cr_{success}) = \sum_{x \in Cr_{success}} (x^n / |Cr_{success}|)^{1/n} \quad (7)$$

3. EXPERIMENTAL RESULTS

3.1. Image thresholding for autonomous deployment

All the algorithms are used to calculate the optimal thresholding values by minimizing the within-class variance of the distribution of intensity levels in a terrain image. ADE_*p*BX is used for finding the threshold values for 2, 3 and 4 level image thresholding and it had been successful in finding the optimal threshold values within minimum iteration. The lake image and the result of 2, 3 and 4 level thresholding on it is shown Figure 1. Since all the nodes are deployed we are unaware of the location of the nodes so we find out the location of the nodes with the help of the beacons as references using ADE_*p*BX. Fifty ADE_*p*BX-based localization experiments are conducted for $P_n = 2$ and $P_n = 5$. The performance metric (N_{N_L}, E_l) is computed for each contestant algorithm and Table 1 shows the mean values of $N_{N_L}$and E_l for each algorithm at the end of four iterations both for $P_n = 2$ and $P_n = 5$.

Figure 1a: 2-level thresholding

Figure 1b: 3-level thresholding

Figure 1c: 4-level thresholding

Figure 1d: Original Lake Image

Table 1: $N_{N_L}$and E_l after end of 4 iterations

	$P_n = 5$		$P_n = 2$	
	(N_{N_L})	(E_l)	(N_{N_L})	(E_l))
SaDE	0.86	0.0838	0.16	0.0123
JADE	0.72	0.0518	0.02	0.0085
CLPSO	1.26	0.2635	0.44	0.0205
ADE_*p*BX	0.48	0.0263	0.00	0.0015

4. ACKNOWLEDGEMENT

This work was supported by the Czech Science Foundation, under the grant no. GA102/09/1494.

5. REFERENCES

[1] R. Storn and K. V. Price, "Differential Evolution - a simple and efficient adaptive scheme for global optimization over continuous spaces", *Technical Report TR-95-012,ICSI*, http://http.icsi.berkeley.edu/~storn/litera.html, 1995.

[2] M. Sezgin and B. Sankur, "Survey over image thresholding techniques and quantitative performance evaluation," *J. Electron. Imag.*, vol. 13, no. 1, pp. 146–168, 2004.

[3] A. Boukerche, H. A. B. Oliveira, E. F. Nakamura, and A. A. F. Loureiro,"Localization systems for wireless sensor networks," *IEEEWireless Commun. Mag.*, vol. 14, no. 6, pp. 6–12, 2007