# Department of Electrical Engineering College of Electrical Engineering and Computer Science National Taiwan University Master Thesis

Real-valued Optimization by Subspace Projection and Multi-armed Bandit Techniques

Chun-Jen Peng

Advisor: Tain-Li Yu, Ph.D.

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# Acknowledgments

I'm glad to thank  $\dots$ 

...

(region of interest) (benchmark) Photoshoot

#### Abstract

This thesis presents a benchmark for region of interest (ROI) detection. ROI detection has many useful applications and many algorithms have been proposed to automatically detect ROIs. Unfortunately, due to the lack of benchmarks, these methods were often tested on small data sets that are not available to others, making fair comparisons of these methods difficult. Examples from many fields have shown that repeatable experiments using published benchmarks are crucial to the fast advancement of the fields. To fill the gap, this thesis presents our design for a collaborative game, called Photoshoot, to collect human ROI annotations for constructing an ROI benchmark. With this game, we have gathered a large number of annotations and fused them into aggregated ROI models. We use these models to evaluate five ROI detection algorithms quantitatively. Furthermore, by using the benchmark as training data, learning-based ROI detection algorithms become viable.



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#### Introduction

## Real-valued Optimization Algorithms

Overview of real-valued optimization

#### 2.1 Covariance Matrix Adaptation Evolution Strategy

#### 2.2 Standard Particle Swarm Optimization

Particle Swarm Optimization was first proposed by ... The swarm intelligence family... However, there are multiple varients of PSO over the years. Standard PSO provides a well defined version of PSO that follows the basic principles. It is intend to be a milestone for future comparison, instead of the best algorithm on the market.

So far, there have been three successive versions of standard PSO: SPSO 2006, 2007 and 2011 The underlying principles of these three versions are generally the same as all PSO varients. The exact formula and implementation are slightly different due to latest theoretical progress.

Initialization of the swarm. The swarm size, denoted as S, differs in SPSO 2006 and SPSO 2011. In both SPSO 2006 and SPSO 2007, the initial number of particles is defined as:

$$S = 10 + |2\sqrt{D}|,$$

where D is the dimension.

However, in SPSO 2011, the swarm size can be defined by user, yet suggested as 40 [2] since the original swarm size is far from optimal.

Each particle in the swarm possesses the following elements: current position, current velocity, personal pervious best position, and previous best position in the neighbourhood.

The information links... The adaptive random topology described in [1] is formally equivalent to "Stocastic Star".

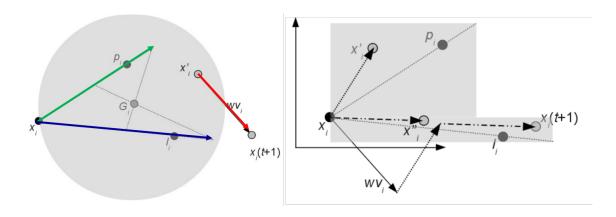


Figure 2.1: (a) SPSO 2011. (b) SPSO 2006.

Update Velocity as shown in Figure 2.1 The pseudo code defined in [5]

#### 2.3 Ant Colony Optimization for Continuous Domain

Ant Colony optimization (ACO) is first proposed by Dorigo [3] to solve combinatorial optimization problems, including scheduling, routing, and timetabling. These problems aim to find optimal combinations or permutations of finit sets of available components. Inspired by the foraging behavior of natural ants, ACO mimics the pheromone deposition of ants along the trail to a food source. The deposited pheromone, which indicates the quantity and quality of the food, creates an indirect communication among ants and enables them to find the shortest paths. The pseudo code of ACO is given in Algorithm 1. Two major procedures: solution construction and phermone update, are detailed in the following paragraph.

Consider a search space S defined over a finit set of all possible solution components, denoted by C. Each solution component, denoted by  $c_{ij}$ , is a decision variable  $X_i$  instantiated with value  $v_i^j \in D_i = \{v_i^1, ..., v_i^{|D_i|}\}$ . To construct a new solution, an artificial ants starts with an empty partial solution  $s^p = \emptyset$ . During each construction step, the partial solution  $s^p$  is extended with a feasible solution from the set  $N(s^p) \in C \setminus s^p$ . The probabilistic pheromone model adopted for selecting a feasible solution from  $N(s^p)$  can be defined as follows:

$$p(c_{ij}|s^p) = \frac{\tau_{ij}^{\alpha} \cdot \eta(c_{ij})^{\beta}}{\sum_{c_{i\ell} \in N(s^p)} \tau_{i\ell}^{\alpha} \cdot \eta(c_{i\ell})^{\beta}}, \forall c_{ij} \in N(s^p),$$
(2.1)

where  $\tau_{ij}$  is the pheromone value associated with component  $c_{ij}$ , and  $\eta(\cdot)$  is a weighting function.  $\alpha$  and  $\beta$  are positive parameters which determine the relation between phermone and heuristic information.

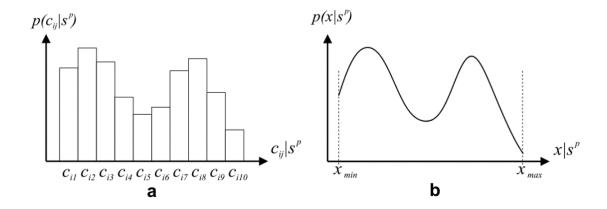


Figure 2.2: (a) Discrete probability distribution  $p(c_{ij}|s^p)$ . (b) Continuous probability density function  $p(x|s^p)$ 

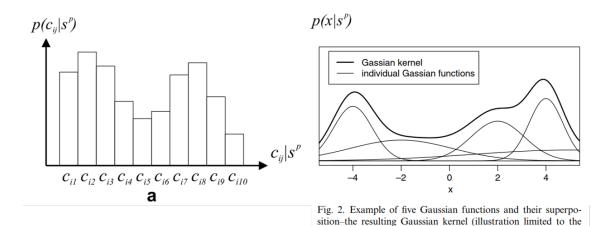


Figure 2.3: (a) Discrete probability distribution  $p(c_{ij}|s^p)$ . (b) Continuous probability density function  $p(x|s^p)$ 

range  $x \in [-5, 5]$ ).

The pheromone update

Over the years, multiple approaches of extending the ACO on continuous domain have been given. One of the most successful version is  $ACO_R$ , proposed by Socha and Dorigo in 2008 [4]. It extends ACO to the continuous domain without making any major conceptual change to its structure. The fundamental idea underlying  $ACO_R$  is the shift from using a discrete probability distribution to using a continuous one, demonstrated in Figure 2.2.

A enhanced Gaussian kernel PDF as shown in Figure 2.3.

#### Algorithm 1: Ant Colony Optimization metaheuristic

```
while termination criterion not met do
schedule activities
solution contruction by ants();
phermone update();
daemon actions();
```

## Multi-armed Bandit Algorithms

Describe the exploration vs. exploitation dilemma.

- 3.1 The Multi-armed Bandit Problem
- 3.2 The Upper Confidence Bound Algorithm
- 3.3 The Price of Knowledge and Estimated Reward strategy

The Price of Knowledge and Estimated Reward (POKER) strategy considers three ideas: pricing uncertainty, exploiting the lever distribution and taking into account the horizon

#### Linear Transformation

Overview of real-valued optimization

- 4.1 Affine Transformation
- 4.1.1 Translation
- 4.1.2 Rotation
- 4.1.3 Scaling
- 4.1.4 Shear
- 4.1.5 Affine transformation matrix
- 4.2 Projective Transformation
- 4.2.1 Homogeneous Coordinate

Augmented Matrix

- 4.3 Optimization for Transformation Matrix
- 4.3.1 (1+1)-ES
- 4.3.2 Loss function

Attention plays an important role in human vision. For example, when we look at an image, our eye movements comprise a succession of fixations (repetitive positioning of eyes to parts of the image) and saccades (rapid eye jump). Those parts of the

image that cause eye fixations and capture primary attention are called regions of interest (ROIs). Studies in visual attention and eye movement have shown that humans generally only attend to a few ROIs. Detecting these visually attentive regions in images is challenging but useful in many multimedia applications, such as automatic thumbnail cropping, object recognition, content-based image retrieval, adaptive image compression and automatic browsing in small-screen devices.

## The New Bandit Technique

Overview of real-valued optimization

- 5.1 Framework of the New Bandit Algorithm
- 5.2 Initialize Clusters
- 5.3 Subspace Projection
- 5.4 Remain Evaluations Allocation

#### 5.5 Recluster

## Experiments

Overview of real-valued optimization

- 6.1 Test Problems
- 6.1.1 CEC2005 25 benchmark problems
- 6.2 Experiment Settings

CMA-ES initial mean and std, population settings SPSO2011 parameters (c, w) settings, and population settings

#### 6.3 Results

#### 6.4 Discussion

#### Conclusion

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