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H. Füger, G. Stein, U. Stilla

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Multi-Population Evolution Strategies for Structural Image Analysis

H. Füger, G. Stein, U. Stilla

Forschungsinstitut für Informationsverarbeitung und Mustererkennung (FIM/FGAN)
Eisenstockstr. 12, 76275 Ettlingen, GERMANY

Abstract

To identify objects in aerial images, a special structural approach, based on a blackboard system, is used. The reference objects are described with generic models and a set of real-valued parameters. To adapt these parameters in an automatical way a closed-loop system is proposed using multi-population Evolution Strategies with a special form of migration. The result of the parameter optimization is demonstrated with an example of identifying bridges in aerial images. Applying this closed-loop system a reduction of computational effort was achieved.

1 Introduction

In order to analyse man made objects in aerial images, a structural method using generic models is implemented. The models are controlled by numerous parameters, which must be adjusted to obtain optimal performance. These parameters typically interact in a complex and non-linear way. As the dependencies between the parameters and thus the fitness function are not known the problem of optimization cannot be described mathematically.

The determination of the parameters is usually done intuitively by the programmer. This procedure is very time consuming, considering, that even for simple applications about fourty parameters must be tuned. For the purpose of generalization a large number of images must be analyzed, so automatization of the parameter optimization was necessary. To solve this problem, a closed-loop system is proposed, using Evolution Strategies (ESs). The ESs use several populations (mpES) and a special form of migration.

First we describe the structural image analysis and the importance of adjusting the tolerance parameters. Then the applied mpESs and the migration scheme are shown. The interactions between the image analysis and the mpESs are explained, and an objective function is defined. Finally the results of the parameter optimization are presented with an analyzed aerial image.

2 Structural Image Analysis

The working scheme for the object analysis includes two processing levels: the preprocessing and the model directed analysis. During preprocessing object primitives (e. g. object LINE) are extracted. Starting with these object primitives the model directed analysis builds up more and more complex objects (e. g. object STRIPE) until the final objects (e. g. object BRIDGE) are generated. In figure 1a the production net of the model BRIDGE is shown.

The data driven analysis is realized as a blackboard system [3, 4, 6, 5]. Each model is implemented as a knowledge source. For each object there exists a symbolic description in the blackboard memory. An individual object is described by several attributes each accepting one value only. For example there are attributes for coordinates, length and width of objects and also an assessment attribute for the similarity of the of object and the model. A selection module selects the next object to be processed (the object with the momentary best assessment) and assigns it to the knowledge sources.

In the knowledge sources the model directed construction, that can be applied, of more complex elements is carried out. For every object exist a production P_i (knowledge source), which generates an object of a higher level (figure 1a). The working scheme of all knowledge sources is identical: starting with the assigned (triggering) object, other objects are data driven searched in the blackboard memory to build up the more complex object.

The search is organized by constructing intervals over the attribute space. This construction of intervals is controlled by model parameters and tolerance parameters. For example there are parameters for constructing two dimensional areas in the search space as shown in figure 1b where stripes of a given width w should be found. The figure 1b i) shows the ideal model conception. Normally the images are corrupted by noise and may have a distortion, one obtains object combinations as in the figure 1b ii). The tolerance parameter Δw has to be adapted, so that the object LL belongs to the search area, but objects, which do not fit the model conception, are not found (see figure 1b iii).

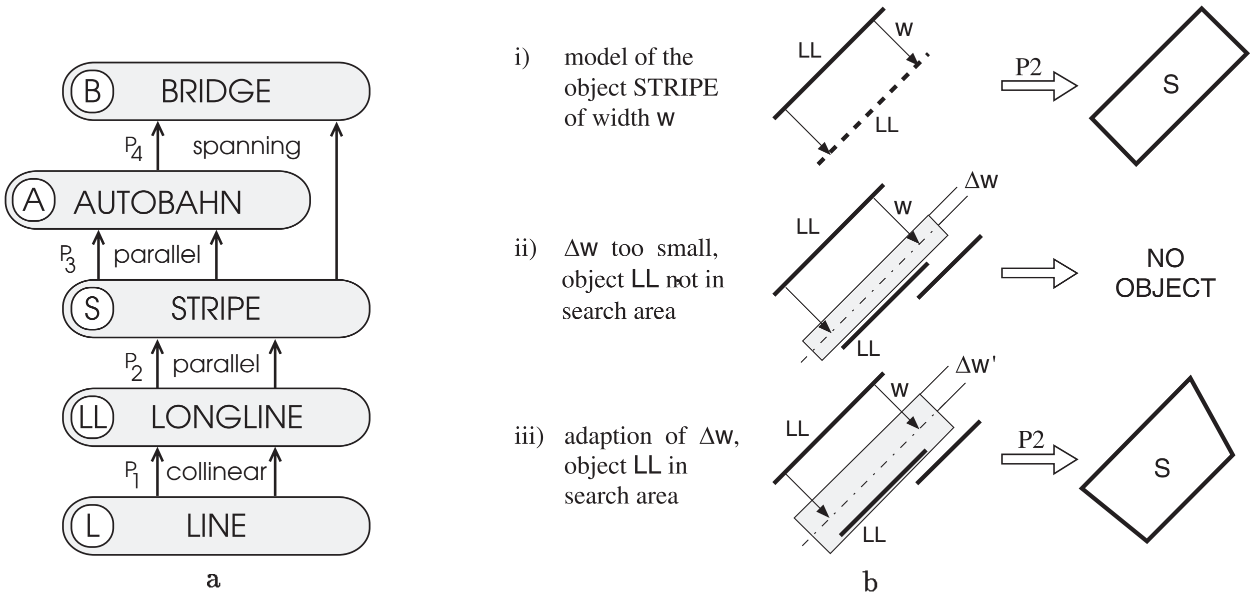


Fig. 1: a) Production net of object BRIDGE, b) Adaption of the search area.

3 Evolution Strategies

Evolution Strategies are optimization algorithms based on the model of natural evolution [7]. To examine the behaviour of different strategies [8, 1], we have implemented four different (μ, λ)-ES (ES_1-ES_4). They differ in the complexity of the scheme for mutation, recombination (crossing-over) and inversion.

In ES_1 one individual of the population is randomly selected, mutated and becomes an offspring. The parent parameter sets are mutated by adding normally distributed random numbers [2]. The ES_2, with a kind of multisexual scheme, combines all individuals of the population and generates the offspring by using mutation. In the ES_3 and ES_4, two individuals are selected, mutated and recombined applying crossing-over. Thus μ individuals are the parents of λ offspring and thereby the imitation of sexual reproduction is possible. Additionaly in ES_4 inversion is applied. Thus, one individual of the recombined individuals is randomly selected and an offspring is generated.

We used a set of n populations pop_i, each containing μ individuals $\mathbf{p}_{ij}$. An individual corresponds to a parameter set $\mathbf{p} = \{p_1, p_2, \ldots, p_m\}$ ($p_{i_{min}} \leq p_i \leq p_{i_{max}}$) and is assessed with a_{ij}. The individuals of a population pop_i are sorted by a and thus there exists a best individual $\overline{\mathbf{p}}_i$ and a worst individual $\underline{\mathbf{p}}_i$. For each population pop_i, the best individual $\overline{\mathbf{p}}_{ig}$, that was reproduced during all g generations, is stored.

Migration is applied, in order to avoid, that populations remain at a non-global maximum or in a wide valley. We implemented a special kind of migration, which is realized as a circle exchange (figure 2). Periodically, $\overline{\mathbf{p}}_{ig}$ of pop_i migrates to pop_{i+1} and substitutes $\underline{\mathbf{p}}_{i+1}$ of pop_{i+1}. The parameter set $\overline{\mathbf{p}}_{ig}$ is stored until a better parameter set $\overline{\mathbf{p}}_i$ is reproduced, and this parameter set substitutes $\overline{\mathbf{p}}_{ig}$.

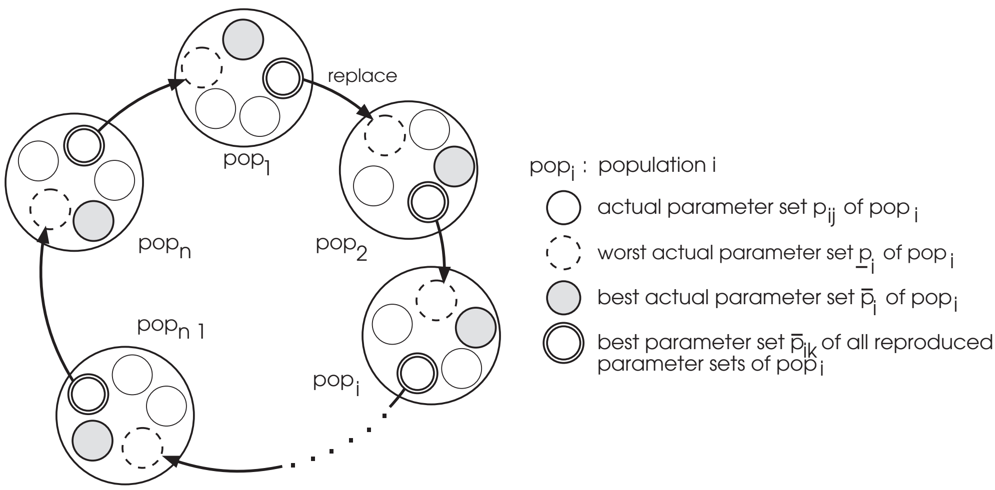


Fig. 2: Migration (circle exchange).

4 Closed-Loop System

In order to obtain an optimal parameter set for a given image analysis problem a closed-loop system (figure 3a) is used. Starting with n populations pop, the image analysis is carried out for each parameter set $\mathbf{p}_{ij}$.

In figure 3b an example visualizes the output of the image analysis. The dotted lines mark the contours of a road and the dashed lines mark the contours of the spanning autobahn. The reference position p_{ref} of the bridge is indicated by a small cross. The production net (figure 1a) generates the objects STRIPE (S) and AUTOBAHN (A), which build up an object BRIDGE. The position p_{out} of the resulting object BRIDGE (figure 1a, P_4) is marked with a cross. Depending on the adjustments of the parameters, the position p_{out} of the object BRIDGE differs from the correct position p_{ref} of the reference bridge, because the generated bridge was built up with the wrong objects.

A simple objective function is used to assess the fitness of the output object BRIDGE. The assessment a of a parameter set $\mathbf{p}$ is calculated using the euclidian distance d between the known position p_{ref} of the reference bridge, the position p_{out} of the generated object BRIDGE and the time t_c (counter of the processed objects) for the image analysis. The relative difference of distance is scaled with k_d and truncated, so we get k_d distance classes. If different distances belong to the same distance class, they are distinguished in the assessment by the counter t_c.

$$a = f(d, t_c) = \left[k_d \left(1 - \frac{d}{d_{max}}\right)\right] + \left(1 - \frac{1}{t_c}\right)$$

If the distance d is greater than a given distance d_{max}, the generated bridge is rejected. The assessment a of each analysis is stored with its active parameter set **p**.

According to the different mpESs randomly chosen parameter sets **p** of pop_i are selected and λ offsprings are generated. For the λ individuals of n populations the image analysis is carried out and the assessment is evaluated. The μ best of the λ offsprings are selected and form the population pop_i of generation $g + 1$. Migration (figure 2) is activated periodically after g_{mig} generation.

The run is terminated, if the assessment a of the output (target object) reaches the termination criterion $a \geq a_{min}$. If this termination criterion is not reached after g_{max} generations, the run is stopped without success.

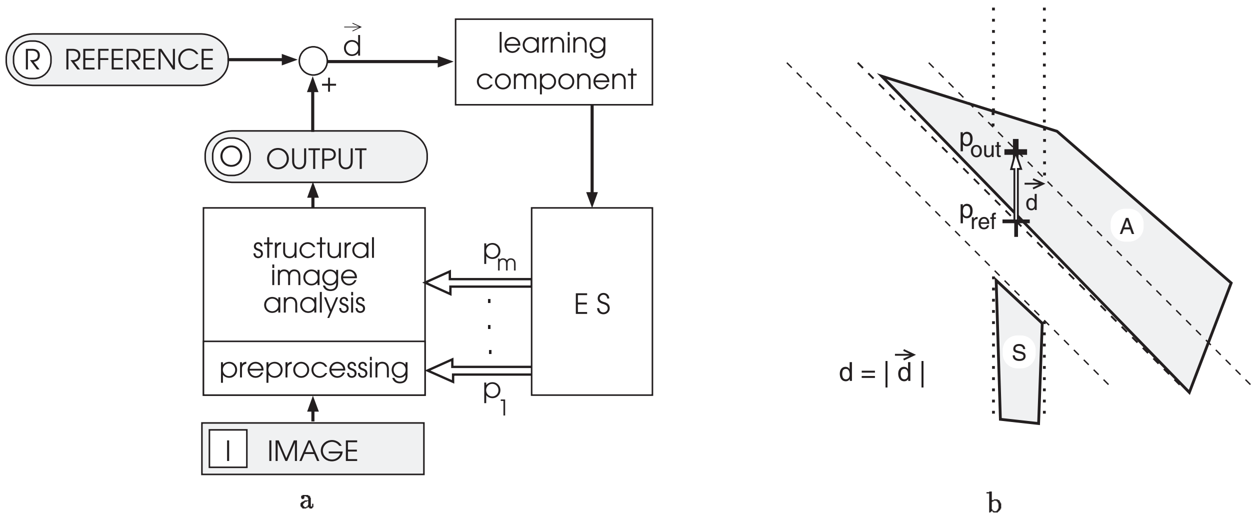


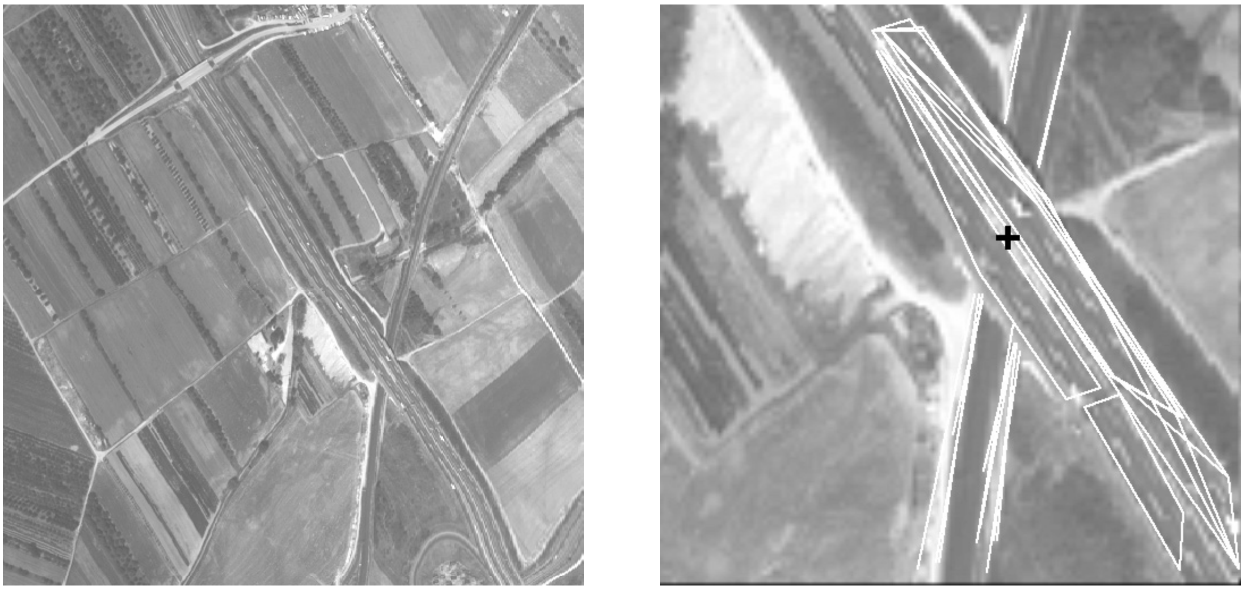
Fig. 3: a) Structure of the closed-loop system, b) Measure of the distance d.

5 Results

For the experiments we used as input data aerial images displaying a suburban region with roads and bridges (figure 4a). A bridge model is described with four productions (figure 1a) and a set of model parameters. The accepted distance d was set to $d_{max} = 20$ and the maximal number of generations $g_{max} = 1000$. The starting parameter values are randomly chosen.

Different runs with the evolution strategies ES_1-ES_4 were used for parameter optimization. For all of these evolution strategies the following parameters were chosen: $n = 4$ populations, $\mu = 5$ parameter sets, $\lambda = 10$ offsprings, $m = 40$ parameters, $g_{mig} = 20$ and $g_{max} = 1000$ generations.

In all evolution strategies the termination criterion $a \geq a_{min}$ was reached approximately after 30 generations. The result of the image analysis with the application of ES_4 is displayed in figure 4b. The position of the generated object BRIDGE is marked with a cross. Additionally the objects STRIPE and LONGLINE, which are partial objects of the object BRIDGE, are shown. The result was generated in $g = 26$ generations and $t_c = 813$ processed objects. In former experiments of evolution strategies (ES_1-ES_4), applying only one population (no migration), the same result required $g = 64$ generations on the average.



a b

Fig. 4: a) Aerial image, b) Final result of the image analysis (detail).

6 Conclusion

For the given image anlysis problem, a closed-loop system for adapting tolerance parameters in an automatical way, was successfully used.

Comparing parameter sets which led to accepted objects BRIDGE with the same distance d, we generally noticed, that objects BRIDGE generated in first generations usually needed more time t_c (more processed objects) than in later generations. This is due to the fact, that the number of object primitives generated, is determined by parameters controlling the preprocessing of the image and that badly adjusted parameters can lead to a drastic increase of the object primitives. During optimization the parameter sets $\overline{p}_{ig}$ of the later generations contain similar values for the preprocessing control parameters .

If the optimization process lasts too long, because the termination criterion cannot be reached, n parameter sets $\overline{p}_{ig}$ may be chosen. These parameter sets can already represent near optimal results.

We used mpESs with a special kind of migration. Future work will examine new schemes of migration, in which more than one individual move or where the chosen individual migrates randomly.

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