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EVOLUTIONARY OPTIMIZATION ALGORITHM WITH LEARNED BEHAVIOR FOR IMAGE RESTORATION

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Abstract. The Evolution Strategy algorithm for maximum entropy image restoration with learned behavior is discussed. Evolutionary algorithms are widely used to search for solutions to "ill-posed" optimization problems. These are based on the simulation of the natural evolution process within a population of individuals. We are introducing a way to drive restoration, without significant impact on the final result in case of misguiding.

Key words: techniques: image processing

1. INTRODUCTION

The image restoration problem refers to the reconstruction of an image, which has been corrupted by noise and probably has undergone blurring. The image needs to be positive on the spectral support, zero outside and compatible with known data. The finite support for initial data leads to the existence of an "invisible" part of a true image distribution and no linear method will recover it. Consequently, the image reconstruction always involves the optimization of some nonlinear objective function and the application of extra information to find true image estimation. The maximum entropy method for image deconvolution (MEM) was introduced by Burg (1975) and utilizes a kind of objective function which allows to choose among all admissible image distributions the one which has the maximum entropy in a resulting solution. The clear physical

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interpretation makes MEM attractive for image synthesis but encounters difficulties in the optimization of highly nonlinear objective functions.

Nevertheless the problem of exploring nonlinear functions is well investigated and addressed via the use of evolutionary search techniques. In previous work (Promislov 1999) the Evolutionary Strategy algorithm for Maximum Entropy image restoration for radio-astronomy data (ESMEM) was proposed and its properties were discussed.

The implementation of the ESMEM lacked the user's influence on the convergence process. For astronomy data the user is often able to circumscribe a possible range for the reconstruction result and it is useful to introduce a mechanism to drive computation in a desirable way without directly affecting the fitness function and so avoiding a premature convergence. The purpose of this work was to generalize ESMEM by using a learned behavior (ESMEMB).

2. THE EVOLUTION STRATEGY ALGORITHM WITH A GUIDING OPERATOR

The image observation model in a lexicographical order is $g = f \otimes h + e$ (where $\otimes$ is the convolution operator), and then the origins of maximum entropy image restoration are based on the following assumptions in the 1-D index notation:

$$\sum_{i=1}^{N} f_i = \gamma \tag{1}$$

$$g_k + e_k = \sum_{i=1}^{N} h_{ik} f_i \tag{2}$$

$$\sum_{k \in A} \frac{e_k^2}{\sigma_k^2} = \Omega \tag{3}$$

$$E_{\text{ent}}(f) = -\sum_{i=1}^{N} f_i \log \frac{f_i}{M_i} \tag{4}$$

where f is a restored maximum entropy image, g is the observed image, h is the point-spread function matrix, e is the estimated observation error, normally distributed with zero mean and σ_k variance,

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γ is the total intensity, A is a region where the data is defined, Ω is a confidence level and M is the default image which determines how the image looks like if there are no data. The entropy to be maximized is the Shannon's entropy (4).

Maximizing (4) in respect to (1–3) using the Lagrange multipliers λ and setting the partial derivatives to zero leads to the well-known expression (Promislov 1999):

$$f_i(\lambda) = M_i \gamma \frac{\exp(-\sum_{k\in A} \lambda_k h_{ik})}{\sum_{l=1}^{N} \exp(-\sum_{k\in A} \lambda_k h_{lk})} \tag{5}$$

Then ESMEMB is an iterative procedure that applies Darwin's evolutionary model to solve an optimization problem and uses learning to incorporate the user's feeling of data and to increase convergence rate. Let us introduce the main definitions to be used.

– The analog elements of $\{\lambda_i\}$ are object variables.

– An individual Λ is a set of parameters $\lambda_i \, dim\{\lambda_i\} = N$, that are defined for a given objective function E_{λ_i}. An individual is fully described by its object variables.

– A population $\{\Lambda_j\} \, dim\{\Lambda_j\} = P$ is a set of individuals with the same objective function E_{λ_i} .

– The selection operator S selects $K\,, K \leq P$ individuals on the evolution step t to be reproduced on step $t+1$ in accordance with a given criterion $\Psi = min\{E_{\lambda_i}\}$.

– The crossover operator C is applied to two individuals on the step t to produce two new individuals on the step $t+1$.

– The mutation operator M^u randomizes small number of object variables in the individual.

– The emotional operator O is applied to population changes in the fitness of the individual but does not affect directly its object variables.

– The energy distribution in the population on the step t is defined as ρ_t.

The full evolution in the chain can be represented as the composition of operators:

$$\rho_t \xrightarrow{S} \rho_t^S \xrightarrow{C} \rho_t^C \xrightarrow{M^u} \rho_t^{M^u} \xrightarrow{O} \rho_t^O \longrightarrow \rho_{t+1}.$$

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In his work of 1896 Baldwin stated that learned behavior and characteristics at the level of individuals together with evolutionary pressure are able to affect the genes significantly. The learning process here any environmentally driven change that leads to the increasing of the fitness for an individual. The algorithm accepts the learned behavior through changes in a default image. The key feature is that these changes are made on phenotypic level and have no direct reflection in the objective variables λ_i of an individual. So they will not be passed on to offsprings through a crossover mechanism. The changes indirectly influencing the genes level of offsprings use the Baldwin Effect and learning.

The default image supplies initial knowledge of the user about how the restored image may look like. For example if the "default" image is flat the ESMEMB tries to make the output image as flat as allowed by the data. The algorithm is constructed in such a way that M before being multiplied to f was modified by adding constant value and rescaling $M' = (M + \alpha * F)/K_M$, where $F \approx 0.7$ is the coefficient controlling the environmental pressure and K_M is the normalization coefficient chosen so that $\sum_{k=1}^{N} M' = 1$. The "simulated annealing" method was used to decrease the strength of the environmental pressure F during the convergence process, compensating the fact that the learning increases the rate at which populations find optima in fixed environments.

3. CONCLUSION

This maximum entropy evolutionary strategies algorithm with emotional guiding has approximately a 30% faster convergence rate then the ordinary one and allows to introduce a priory knowledge to drive restoration, without significant impact on the final result in case of misguiding.

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