Interactive Evolutionary Strategies for Automatic Facial Composite Generation

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ABSTRACT

The main aim of this project is to develop and analyze a program for the automatic face generation through interactive evolutionary strategies (IES). The user selects a number of images based on their similarity to a target image from a set of images presented to him via the interface. The generation of the facial images at each iteration are achieved by performing parent selection, recombination, mutation and survivor selection steps of evolutionary strategies (ES) and optimizing the T dimensional parameter vector of an active appearance model based on the selections of the user interactively. The main goal is to continue the iterations until the user is satisfied with at least one of the generated images. The program has been implemented and the preliminary tests show that IES gives successful results.

Categories and Subject Descriptors

I.2.8-Problem Solving, Control Methods and Search

General Terms

Design, Algorithms, Human Factors

Keys

Evolutionary strategies, interactive evolutionary strategies, computerized facial composite generation, active appearance model.

1. INTRODUCTION

In this project, we implemented an interactive evolutionary strategies (IES) [1][2][3] approach to generate the facial images interactively, optimizing the T dimensional parameter vector of an active appearance model (AAM)[4]. Parent selection, recombination, mutation and survivor selection steps of ES are performed. The performance of the approach is evaluated through a series of tests. The performance of IES shows us how suitable the ES approach is for using interactively. When evaluating the performance of the method based on the user interface, the factor of the user must be considered because the method is interactive. A user provides the fitness evaluation, so this evaluation is subjective, i.e. a user may give different fitness values to the same image at different trials. Also a user gets tired, becomes bored and fails to pay attention if has to evaluate too many images. So, the method may not give a good performance in the interactive case even though it may be very successful when used in the non-interactive mode.

In the second section, the IES based approach will be explained. Section 3 will provide the experimental results. The section 4 will conclude the paper and will give pointers to future work.

2. THE PROPOSED AUTOMATIC FACE GENERATION THROUGH EVOLUTIONARY STRATEGIES

In order to determine the parameter vector of the active appearance model [4] for a target image, we used an interactive evolutionary strategies approach (IES) [1][2][3].

IES is applied through a user interface [5] we implemented for this project. The randomly generated initial images are shown to the user on the screen. There is a check-box under each image. The user selects a pre-determined number of images which are similar to the target image by using these check-boxes. After selection, user clicks the “Run” button and the selected images are processed by the IES algorithm, parent selection, recombination, mutation and survivor selection steps are performed. When the iteration ends, new images are displayed on the screen. The user selects the images which are similar to the target face again. This cycle is repeated by clicking the “Run” button. Whenever the user is satisfied with at least one of the displayed images, he clicks the “Stop” button. The last selected images are shown on the screen. Finally, the user selects the one final image which is most similar to the target and hits the “Finish” button to complete the process. This selected image is displayed on the screen as the generated solution.

2.1 Evolutionary Strategies

The ES [1][2][3] algorithm works on a population of individuals. The initial population is generated randomly. Each individual has a chromosome which is a vector of real-valued numbers. Chromosomes consist of two parts: Object variables which are the genes ($x_1, \dots, x_n$) and strategy parameters which are the mutation step sizes (deviations) ($\sigma_1, \dots, \sigma_n$). Each choromosome represents a possible solution of the algorithm to find the target member. μ represents the number of individuals in a population (parents). From this population, children are generated. λ represents the number of children. In order to generate λ children, parent selection, recombination and mutation steps are done serially for λ times. These steps will be explained in further detail below. After the children are created, survivor selection step is performed. In this step, survivors are selected from the set of children only or from the set of parents and children based on the chosen strategy. After survivor selection, selected individuals form the new population. The following steps outline the basic process of generating a new population from an existing population.

1. Parent Selection: Two parents are selected randomly.

2. Recombination: Recombination generates one child from the selected two parents. There are two types of recombination used in this study: Discrete recombination which selects one of the parental values (z_i is x_i or y_i chosen randomly) and Intermediary recombination which averages parental values ($z_i = (x_i + y_i) / 2$). In order to determine if recombination will be performed, a random number between 0 and 1 is generated and if it is less than or equal to a pre-determined value P_c, then discrete recombination is done for genes, intermediary recombination is done for deviations. Otherwise, one of the parents is selected randomly and genes and deviations of the selected parent are copied to the child.

3. Mutation: Uncorrelated mutation with n step sizes method is used. First, mutation step sizes are mutated ($\sigma \rightarrow \sigma'$):

   $$\sigma'_i = \sigma_i \cdot \exp(\tau \cdot N_i(0,0.3))$$

   where τ is $1/(2n^{½})^{½}$. Then, genes are mutated ($x \rightarrow x'$) using the new step sizes:

   $$x'_i = x_i + \sigma'_i \cdot N_i(0,0.3)$$

   If a new gene or mutation step size value exceeds the pre-determined boundary values, mirroring is performed.

4. Survivor Selection: There are two types of survivor selection strategies. In (μ, λ) selection (comma strategy), selection takes place on the set of children (λ offspring) only and their parents are discarded. In ($\mu + \lambda$) selection (plus strategy), selection takes place on the set of parents and children combined. Selection is performed by ranking the fitness values of the individuals and selecting μ of them.

All these steps are performed until an individual which is similar enough to the target individual is found.

Pseudocode of an ES Algorithm:

```
generate initial population randomly
repeat
   repeat λ times
       randomly select 2 parents
       perform recombination
       perform mutation
   end
   perform survivor selection
until stopping criteria are met
```

2.2 Interactive Evolutionary Strategies

In an ES, the fitness of an individual has an effect only in the survivor selection step. In the interactive version of the algorithm, a fitness function is not used and the survivors are directly determined by a user. When the images of the population are shown to the user, some of these images are selected. The selected images are the fittest ones, so they form the new population. A user can stop the run of the algorithm and finish the process whenever he is satisfied by at least one image generated by the IES. Therefore the stopping criterion is based on the satisfaction of the user with the displayed images.

2.3 Implementation Details

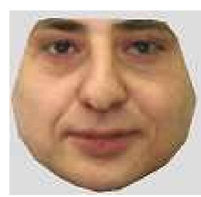
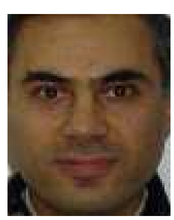
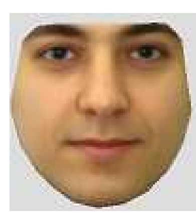
In this study chromosomes represent a set of AAM [4] parameters which define an image. Based on our model, these parameters are real numbers in the range of [-0.3,0.3]. Each chromosome has 17 genes and 17 mutation step sizes represented as real numbers. μ which is the size of the parent population is selected as 4 and λ which is number of children generated at each iteration is chosen as 16. The cross-over probability pc is 0.8. A (μ,λ) strategy is used which means that the new population consisting of 4 individuals is selected from among the 16 children only. Self-adaptive mutation parameter τ is chosen as $1/(2n^{½})^{½}$.

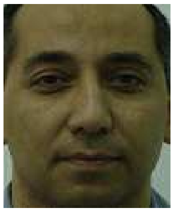
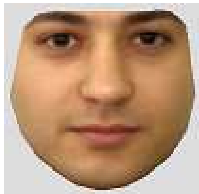
3. EXPERIMENTS

The ES algorithm is tested for generating 4 different faces by 8 testers. Two of these faces belong to people who are well known by the testers and are also in the image database [5]. The third face belongs to a person well known by the testers but is not in the image database [5]. The last face belongs to a person who is not known by the testers, but is seen very briefly and also is not included in the image database [5].

After the testing stage, the vectors representing the 8 images, which are generated by the 8 testers, are averaged to obtain the mean image. All these images determined to be the best, have been generated in 5 iterations of the IES on average. This means that since at each iteration, a user selects 4 out of the 16 images shown on the screen, a total of 80 images have been viewed and evaluated.

The resulting mean images are shown to 10 people, who know the four people used as the target faces well, and are asked to recognize the images. The target images, generated images by IES and the resulting recognition rates are given below.

Target Image	Generated Image	Recognition Rate
		100 % This person is well known by the testers and his picture is in the database
		30 % This person is well known by the testers and his picture is in the database

		60 % This person is well known by testers and his picture is not in the database
		40 % This person is not well known by the testers and his picture is not in the database

The first generated image is recognized at a rate of 100 % and the recognition rates of the latter three generated images are lower. We think that this is due the fact that the face of the first person has some distinctive characteristics whereas the other three do not and their features are very similar.

4. CONCLUSION AND FUTURE WORK

In this study, the IES implementation is successfully completed. The preliminary results show that the proposed solution works fine for our small face image database. We plan to determine the AAM model parameters [4] better and to test the proposed algorithm on a larger database of facial images.

For the proposed program to be fully functional and for it to be able to compete with similar programs such as EvoFIT [5] and EigenFIT [5], several enhancements can be made, such as allowing the editing of the shape, size, placement of the parts on a face during a run and reflecting this onto the solution vector; building models of each face part separately and freezing the changes in a face part when it is determined to be similar to the corresponding face part in the target image by the user while other parts are still allowed to change; finally allowing accessories like hair, hat, eyeglasses, etc. to be added to the images for better recognition.

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7. REFERENCES

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