A GENETIC ALGORITHM FOR LEARNING IMAGE BLUR AND SHARPEN FILTERS

Dr. Sarab M. Hameed

University of Baghdad\ College of Science Computer Science Department Sarab_majeed@yahoo.com

Abstract

This paper presents an approach for learning traditional image filters (blurring and sharpening). The concept of learning is based on the mechanism of Genetic algorithm (GA). By GA, filters applied on one *source* image can be learned and then used to process automatically another *target* image. By this way, blurring and sharpening can be implicitly deduced and applied without requiring to mathematically defining (i.e. explicitly) them. The proposed approach is simple and can provide good results; however, applying the filter directly is much more efficient.

Keywords: Genetic algorithm, blur, sharpen, image analogy.

Introduction

There are, commonly, three models for computer learning [1]. One approach models learning as acquisition of explicitly represented domain knowledge. Based on its experience the learner constructs or modifies expression in a formal language, such as logic, and retains this knowledge for future use.

approach is The second neural or connectionist networks which represent knowledge as patterns of activity in network of small, individual processing units. Inspired by architecture of animals the brains. connectionist network learn by modifying their structure and weights in response to training data.

The third approach is genetic learning approach which inspired by genetic and evolutionary analog. This approach to learning through adaptation is reflected in genetic algorithms, genetic programming, and artificial life research. Genetic algorithms begin with population of candidate problem solution. Candidate solutions are evaluated according to their ability to solve problem Only the fittest survive instances. are combined with each other to produce next generation of possible solution.

In the few years ago, researches are interested in transferring properties from one image to another. One such algorithm is of Hertzmann et al. called image analogies [2]. Image analogies are a new framework that uses machine learning and various methods in order to learn and apply filters to an image. In practice image analogies includes two stages: a design phase and application phase in order to produce the desired output. In design phase a pair of images A, and A', is used as training data where A is the original and the other is a filtered version of that one; and an application phase, in which the learned filter is applied to some new target image B in order to produce analogous filtered result B'. Image an analogies algorithm provide a very natural means of specifying image transformations. In a boarder context, image analogies are based on various algorithms from different areas. It combines techniques from machine learning, rendering and texture synthesis of Ashikhmin [3] and Wei and Levoy's work [4]. Ashikhmin presents a simple pixel-based texture synthesis and transfer algorithm that is well-suited for a specific class of naturally occurring textures. The algorithm starts from a sample image and generates a new image of arbitrary size the appearance of which is similar to that of the original image. Similar research as image analogies has been done by Freeman et al. [5] where they use Markov Random Fields (MRFs) for scene learning.

This paper presents a Genetic Algorithm (GA) to blur or sharpen an image. Rather than using an explicit filter, the mechanism of GA is used as learning strategy to learn a filter implicitly from one source image and then apply the learned filter to a new target image. The paper is organized as follows. Section 2 describes how we use GA to learn blur and sharpen filters and how to process an image to get a filtered one. Section 3 and 4 present some results for highlighting the use of GA and conclusions respectively.

GA for Filtering an Image

A genetic algorithm is general method of solving problems to which no satisfactory, obvious, solution exists. It is based on the idea of emulating the evolution of a species in nature and so the various components of the algorithm are roughly analogous to aspects of natural evolution. GA is especially useful for problems without strict solution in which is enough to find a good solution but not necessary the best. In this section, we exploit the mechanism of GA to learn the blur and sharpen filters and then to apply them to target image. From a training pair of images source A and its filtered image A', the GA attempts to learn the filter that is used in A to produce and then uses this learned filter to filter another target image B to get filtered target image (B'). The following subsections clarify GA work and its components.

Individual Description

GAs are search algorithms based on the mechanism of natural selection and natural genetics. The GA evolves a population of individuals. The population represents a set of candidate solutions to the problem at hand, therefore we need to represent the solution that represents individual genotype. In our problem, each solution is represented as a two-dimensional array of $h \times w$ genes where h and w identifies, respectively, the height and width of the target image, B.

Gene (i,j) of an individual is an index to the luminance value of a pixel in the source image, A. GA begins with a populations of individuals. The number of individuals in the population represents the population size, P_s , and it is randomly selected. Each individual represents one candidate solution to the filtering process applied on B.

Objective Function

After preparing a number of individuals, the objective function should be defined that qualify each individual in the population's solution. To calculate the objective function, all A, A', and B images must be converted from RGB color space to a de-correlated color space (YIQ de-correlated color space is used). Then, compute the pixel-wise luminance difference between a neighborhood (we use window of size 3×3) of a source pixel and a target pixel as formulated in equation 1.

diff (gene_{i,j}) =
$$|N_B(p) - N_A(q)|$$
(1)

where:

 $N_B(p)$ is the neighborhood of pixel p in B. $N_A(q)$ is the neighborhood of pixel q in A. $p \in B$, located at coordinate i,j (i.e. p is B(i,j)). $q \in A$, referred to by *gene*_{i,j}.

Then the objective function of GA individual is computed as a sum of *diff* over all genes as formulated in equation 2:

$$obj(idividual) = \sum_{i=1}^{h} \sum_{j=1}^{w} diff(gene_{i,j}) \dots (2)$$

GA Operators

After evaluating the objective function for each individual, a collection of individuals who will have the right to reproduce themselves into future generations can be formed. In this work, we use the binary tournament selection [6, 7]. In tournament, a pair of individuals is competed. The individual with lowest objective function is copied into the mating pool. This process is repeated until the mating pool is filled with number of individuals equal to population size.

Then a crossover operator is performed which operates with probability P_c . In this paper, a pair of individuals produces a single new individual. The genes of the two contributor individuals are compared and the new individual contains the genes that have the smallest error (i.e. $diff(gene_{i,j})$). Figure (1) illustrates the adopted crossover.

Finally, the mutation operator is applied, mutation arbitrary alters one or more genes of the selected individual, by random change with a probability equal to the mutation rate P_m . After applying these three operators the new population for next generation is obtained.

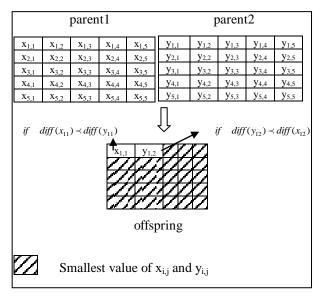


Fig. (1): Crossover operator: offspring contains genes that have smallest errors of the parent.

GA Solution: Filtered Target Image

Actually, we want to apply a blur, or sharpen filter to a given image, such that the only affected information of the image is: it's achromatic or intensity vector. The chromatic or color information of the image does not require to be changed by the filter. Hence we want to preserve the chromatic components of the target image (here represented by I and Q channels) and change only the filtered Y channel. GA is used to learn the Y channel and to browse it form A' image to be applied to B image to get image B'. Then, we convert the obtained component YIQ to RGB color space and hence, the filtered target image is provided.

Experimental Results

The proposed GA is used to blur or sharpen an image. The GA parameters including P_c, P_m, and P_s are set to 0.8, 0.1, and 50 respectively. Fig.(2) depicts some results of GA. The images in the figure are arranged as follows. The first column is for source image A and beneath each one are blurring and sharpening images A_1' and A_2' respectively obtained from applying filters directly. The second column is for target image B and under each one are blurring and sharpening images, B'_1 and B'_2 respectively that are obtained by the proposed GA. Fig.(3) illustrates a comparison between our results and applying filter directly results. Mean Square Error

(MSE) is used to qualify the GA vs applying filter directly results. The 1^{st} column presents original image, the 2^{nd} column depicts GA results, the 3^{rd} column illustrates applying filter directly, and 4^{th} column is MSE.

From results, we one can deduce that GA result is comparable to that result obtained from applying filter directly. However applying filter directly is more efficient since its take few second. On the other hand, GA takes time from 57 to 274 second when applied on different images size from 75 x 85 to 198 x 135 pixels.

Conclusion

In this paper, we have presented a simple GA approach to automatically apply blur and sharpen filter to the target image based on filtered source image. The luminance channel is used as a similarity metric between two different images and is produce acceptable visual results. Moreover, GA is used to reduce the number of comparison instead of full searching for the best match for each target pixel, however, applying the filter directly is more efficient.

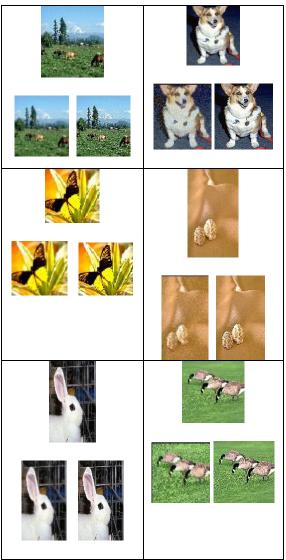


Fig. (2) : Some results of the GA.

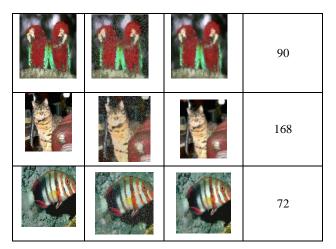


Fig. (3): A comparison between GA and applying filter directly results.

References

- [1] G. F. Luger, W. A. Stubbfield, "Artificial Intellgence Structure and Strategies for Complex Problem Solving", Addison Wesely Longman, Inc., Third edition, 1998.
- [2] A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless and D. H Salesin, "Image Analogies", Proceedings. ACM Press/ ACM SIGGRAPH, 2001, pp 327-240.
- [3] M. Ashikhmin, "Synthesizing natural textures", ACM Symposium on Interactive 3D Graphics, 2001, pp 217-226.
- [4] L. Y. Wei and M. Levoy, "Fast texture synthesis using tree-structured vector quantization", Proceedings of the 27th annual conference on Computer graphics and interactive techniques. ACM Press/Addison-Wesley Publishing Co, 2000, pp 479–488.
- [5] W. T.Freeman W.T, E.C. Pasztor and O.T. Carmichael, "Learning Low-Level Vision", International Journal of Computer Vision.2000, Vol. 40, Issue 1, pp 24–57.
- [6] M. Mitchell "An Introduction to Genetic Algorithm" MIT press, 1996.
- [7] D.E. Goldberg, "Genetic Algorithm in Search Optimization and Machine Learning", Addison Wesley, 1989.

الخلاصة

