EVOLUTIONARY ALGORITHMS FOR TRANSFERRING PROPERTIES BETWEEN IMAGES PART I: GRAYSCALE IMAGE COLORIZATION

Dr. Bara'a Ali Attea
Computer Science Department, niversity of Baghdad

Aminna Dahim Aboud
Computer Science Department, niversity of Baghdad

ABSTRACT
In this paper, an evolutionary algorithm (EA) for "colorizing" grayscale images is introduced by evolving color patch transfer process between a source colored image and a target grayscale image. As the general problem of inverting a gray palette to a color palette is a severely under-constrained, ambiguous problem and has no exact, objective solution, human labor and costly semantic knowledge are required. The presented EA attempts to minimize the amount of human work by automatically choosing colored patches from the source image and applying their colors to the grayscale patches of the target image. Furthermore, the best patch matching over all EA parent individuals are recombined in a single multi-sexual recombination scheme to form a single offspring individual. Mutation, on the other hand, forms all other EA individuals. The simple technique of the proposed EA can be successfully and efficiently applied to a variety of images.

الخوارزميات التطورية لنقل الصفات بين الصور الجزء الأول: تلوين الصور الرمادية

الخلاصه
يهتم هذا البحث بأيجاد خوارزميات تطورية لحل مشكلة نقل الصفات بين الصور. في هذا الجزء نقدم خوارزمية تطورية تلائم مشكلة نقل الألوان من صورة مصدر ملونة الى صورة هدف رمادية. تعتمد الخوارزمية التطورية المقترحة على نقل رقع من الألوان من الصورة المصدر الى الصورة الهدف في آن واحد. يرجع سبب أختيارنا الخوارزمية التطورية الى طبيعة مشكلة التلوين نفسها, حيث تعد هذه المشكلة من المشاكل الغامضة والتي لاتمتلك الى حل صحيح ودقيق. الخوارزمية التطورية المقترحة تحاول التقليل من التدخل البشري في عملية التلوين بوساطة الأختيار الأتوماتيكي للرقع الملونة من الصورة المصدر ونقل الوان هذه الرقع الى الرقع الرمادية للصورة الرمادية. أقترحت طريقة التزاوج متعدد الأجناس لخلط أفضل الرقع المتطابقة لتوليد فرد واحد. من جهة أخرى، تتولى عملية الطفرة الوراثية توليد بقية الأفراد للجيل الجديد. طبقت الخوارزمية المقترحة بنجاح وبكفاءة على أنواع مختلفة من الصور.

KEYWORDS

Image colorization, genetic algorithm, multi-sexual crossover, color patch

INTRODUCTION

Colorization is a useful technique in increasing the visual appeal of black-and-white photos, classic movies or scientific visualizations. Further, colorization has applications in color editing and compression. The problem of coloring a grayscale image involves assigning three-dimensional (RGB) pixel values from a source, color image to a target, grayscale image whose pixels are varied along only one dimension (luminance). As several hues and/or saturation levels may carry the same luminance value, colorization problem has no inherently correct solution. Moreover, it has several other challenges including ambiguity, fuzzy boundary identification, and user expert. [1] [2]. In other words, colorization is in general a severely under-constrained and ambiguous problem for which it makes no sense to try to find an ”optimum” solution, and for which even the obtainment of “reasonable” solution requires some combination of strong prior knowledge about the scene depicted and decisive human intervention. Even in the case of pseudo coloring, where the mapping of luminance values to color values is automatic, the choice of the color map is commonly determined by human decision.

Several techniques are published for digital colorization. Readers please refer to recent papers. Some (but mostly used) colorization work are color transfer of Reinhard et al [3], image analogies of Hertzmann et al [4], the classical full search of Welsh et al [5], and the Antypole strategy of Di Blasi and Reforgiato [1]. The main concept of these colorization techniques is to exploits textural information. For example, the work of Welsh et al, which is inspired by the color transfer [3] and by image analogies [4], examines the luminance values in the neighborhood of *each pixel* in the target image and add to its luminance the chromatic information of a pixel from a source image with best neighborhoods matching. This technique works well on images were differently colored regions give rise to distinct textures. Otherwise, the user must specify rectangular swatches indicating corresponding regions in the two images. Di Blasi and Reforgiato [1] propose an improvement to Welsh et al work, where Antipole clustering strategy is adopted as an efficient data structure for fast color retrieving. Their approach provides a way to speed up the searching process but at the expense of increasing implementation complexity.

In this paper, the technique of evolutionary algorithms (EAs), probabilistic search algorithms based on the model of natural evolution will be applied, for colorization problem. The procedure of evolution works by minimizing the matching error (in term of luminance and texture information) between pairs of source and target square patches. Then transfer color mood from the best evolved source patches to the target patches. In what follow, the characteristic components of this EA will be presented.

THE PROPOSED EVOLUTIONARY ALGORITHM

An Evolutionary Algorithm (EA) is inspired by biological evolution, and is widely believed to be an effective global optimization algorithm. There are a variety of evolutionary algorithms emerged:”evolutionary programming-EP” [6], “evolution strategies-ESs” [7] and “genetic algorithms-GAs” [8]. Moreover, since EAs are motivated by natural principles, when faced with problem, natural remedies are often emulated.

An EA consists of a population of individuals, which are evaluated using fitness function. The individuals (mostly fittest individuals) are reproduced and perturbed via three main EA's operators: selection, recombination, and mutation. The processes used to select which parents will produce offspring varies significantly from one EA to another, and includes strategies such as uniform random selection, rank-proportional selection, and fitness-proportional selection. In addition to these selection processes, the mechanisms used for offspring reproduction also varies. They range from asexual reproduction with no mutation (in which offspring are exact replicas of parents), asexual reproduction with mutation, to sexual reproduction with recombination. Moreover, sexual reproduction can be in either local form with 2-parent recombination or global form with multi-parent recombination. Historically, the EP and ES communities have emphasizes asexual reproduction while the GA community has emphasized sexual reproduction.

In the proposed EA, square patches of pre-selected size- $w_p \times w_p$ - of the target, grayscale image are colorized from suitable $w_p \times w_p$ source patches. The evolution of the patch colorization scheme is manipulated by formulating individual representation, penalty function, and individual evolution via perturbation operators.

Search space representation

In order to apply an EA to a particular problem, it is appropriate to select an internal representation of the space to be searched and define an external evaluation function, which assign utility to candidate solutions. Both components are critical to the successful application of the EA to the problem of interest. Here, to represent a solution (an individual's genotype), a two-dimensional array of $m \times n$ genes is used such that:

$m = h_t / w_p$, and

$$n = w_t / w_p \qquad (1)$$

Where

h_t : Height of the target grayscale image,

w_t : Width of the target grayscale image, and

w_p : Patch width (e.g., we use $w_p = 3,\ 5,\ 7,\ 9,$ or 11).

Gene (i, j) of an individual identifies an un-overlapped $w_p \times w_p$ target patch (i, j) and can contain x and y coordinates of the center of a $w_p \times w_p$ source patch. To start the EA, a population of p_{size} individuals is randomly created, and each individual can represent the genotype of a potential solution to the colorization problem.

The total number of possible solutions represents the search space size (which here, grows exponentially as increasing the number of un-overlapped source patches).

Penalty function

Next, it is important to define a suitable penalty function which rewards the right kinds of individuals. For the colorization problem reported here, it would be desirable to minimize luminance matching error between pairs of target patches and source patches. In other words, each gene (i, j) in an EA individual has associated with it a luminance matching error (i, j) computed as:

$$error(i, j) = match(p_t(i, j), p_s(i, j)) \qquad (2)$$

Where:

$p_t(i, j)$: Target patch being identified by the gene (i, j) ;

$p_s(i, j)$: Source patch referred to by the gene (i, j) ;

and the $match$ between two patches p_t and p_s of a given gene (i, j) is defined to be:

$0.5|\mu_s(i,j)-\mu_t(i,j)|+0.5|\sigma_s(i,j)-\sigma_t(i,j)|$ (4)

Where μ and σ are the luminance average and standard deviation both taken with respect to a $w_p \times w_p$ source or target patch as referred to by subscript *s* or *t* respectively. Then, an EA individual has a penalty function E computed as the sum of all its gene luminance matching errors:

$$E = \sum_{i=1}^{m}\sum_{j=1}^{n} error(i,j) \quad (5)$$

In order to match luminance information, both source and target images must be converted from RGB color space to a de-correlated space (de-correlated YIQ color space is used here).

<u>Evolutionary operators</u>

In our EA, we breakdown the traditional views found in the EA communities and make a hybrid collection of evolutionary processes that would be useful for the colorization problem. The main issues made in the proposed EA are: extinctive selection, single multi-sexual discrete recombination, and preservative mutation operator.

The first character of the proposed EA is the strict denial of selection process; letting all offspring to be created from all parents using recombination and mutation. First a multi-sexual discrete recombination process is applied among all parents to produce only one mated offspring. Genes among all parents are competed and the best ones (with smallest matching errors) are inherited to that offspring.

Next, mutation is used to fulfill the new population with $p_{size}-1$ new offspring. 90% offspring are created by mutating the genes of the mated offspring while others 10% offspring are created randomly from the total search space.

<u>Genotype decoding: phenotype re-coloring</u>

After stopping the EA to a pre-selected maximum number of generations, a population of individuals that may have some promising solutions is obtained. The best individual (with smallest *E*) has to be decoded to its colored result. In EA literatures, the output of the genotype decoding is normally known as phenotype. Here, phenotype coloring includes the following sequence of steps:

1. Go through the best EA individual genes and the target image in scan-line order in steps of one gene (for the individual) and one $w_p \times w_p$ patch (for the target image).
2. Select from the source image a $w_p \times w_p$ patch in which its center has coordinates *x* and *y* referred to by the current gene.
3. For each pixel in the target patch, search the selected source patch in scan-line order for the closest pixel (in term of luminance value). Add the chromatic components (I and Q) of that pixel to the luminance value of the current target pixel.
4. Repeat the sequence 1, 2, and 3 for all target patches.
5. Transform the target image from YIQ to RGB color space to display the result on the screen.

EXPERIMENTAL RESULTS

This section reports some results obtained by running the proposed EA with $p_{size}=40$ to a maximum number of generations equals to 30 for coloring a range of image domains with different sizes. Generally, the experimented images are classified as homogeneous ones. These images include a single object in the foreground and this object is clearly discernible from a mostly homogeneous background. First, (if needed) luminance histogram matching of Hertzmann et al [4] is applied to match the first- and second- order statistics of the luminance distribution of the source image according these of the target image. More concretely, if $l(p)$ is the luminance of a pixel in the source image, then we remap it as

$$l(p)' = \frac{\sigma_t}{\sigma_s}(l(p) - \mu_s) + \mu_t \qquad (6)$$

EA results are compared with the Welsh et al classical full search method [5] (both are implemented using un-optimized visual Basic code.) The neighborhood statistics required in both algorithms are pre-computed over the source and target images. In the full search method, we need to pre-compute neighborhood average and standard deviation of each pixel, while in the EA; the statistics are needed for each un-overlapped patch. Different patch size was used. Obviously, decreasing patch size results in more acceptable results but at the expense of increasing maximum required number of generations. Each EA result is formulated by depicting the phenotype of the best individual obtained after only 30 generations together with the result of the full search algorithm (see figures 1 and 2). Quantitative EA results are also pointed out by including average of penalty function ($E / m*n$) of the best individual in the initial and the last generations. Processing time required for a single Pentium IV PC computer is also included for both colorization algorithms (see table 1). Actually, EA algorithm requires less computation time than presented in the table. By comparing EA results with those of Welsh et al, we can easily demonstrate that the proposed easy to implement EA can produce visually accepted results in a number of image domains although there are some failure (yet tolerable) patch colorization cases. Running time will vary depending on the patch size, size of source and target images (total search space size), p_{size} and the maximum number of generations. In most of experimented results, the computation time of EA colorization algorithm to obtain visually accepted results was better than the classical full search algorithm of Welsh et al.

CONCLUSIONS

This paper introduces a simple colorization technique based on combing the concept of evolutionary algorithms with a patch-based luminance matching strategy. A new multi-sexual recombination strategy is given to recombine, in a single EA step, the best patches found between source color and target gray images. Without user expert, the algorithm can give pleasing visual results for homogenous images. Both EA and patch-based luminance matching could be the subject of future research. For example, try to test this colorization algorithm on more complicated images, i.e. heterogeneous images where the scene has multiple objects on the foreground, or has a cluttered background, or is illuminated in an uneven way.

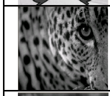
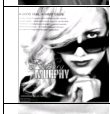
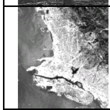
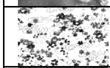
REFERENCES

[1] G. Di Blasi, and R. D. Reforgiato, "Fast colorization of gray images", *In proceedings of Eurographics Italian Chapte,* 2003.

[2] L. F. M. Vieira, R. D. Vilela, and E. R. Nascimento, "Automatically choosing source color images for coloring grayscale images", *16th Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI 2003), Sao Carlos, Brazil. IEEE Computer Society*, ISBN 0-7695-2032-4, pp. 151-158, 2003.

[3] E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley, "Color transfer between images", *IEEE Transactions on Computer Graphics and Applications 21*, 5, pp. 34-41, 2001.
[4] A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless, and D.H. Salesin, "Image analogies", In *Proceedings of ACM SIGGRAPH 2002*, pp. 341-346.
[5] T. Welsh, M. Ashikhmin, and K. Mueller, "Transferring color to grayscale images", *ACM Transactions on Graphics 21*, 3 (July) 2002, pp. 277-280.
[6] J.R. Koza, *Genetic Programming: on the programming of computers by means of natural selection.* Cambridge, MA: MIT Press, 1992.
[7] H.-P. Schwefel, *Numerical Optimization of Computer Models.* New York: John Wiley & Sons, 1981.
[8] D.E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning.* New York: Addison Wesley, 1989.

Table (1). Mean of penalty and processing time comparison between EA and full search.

Target image	$E / m*n$		Time (sec.)	
	gen. no.0	gen. no.30	EA	Full search
	77.565	0.644	1225	2918
	55.686	0.670	964	2086
	393.646	8.673	1121	3061
	217.278	3.129	398	417
	62.396	3.161	444	552
	489.798	13.854	482	534
	363.182	12.938	653	733
	469.055	11.7	235	333
	359.201	18.7	575	688
	493.716	13.410	565	697
	656.273	13.788	279	324
	43.373	1.059	529	812