A Genetic Algorithm Approach for Photomosaic Generation

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ABSTRACT

Photomosaic is an image filled with tiles of smaller images. It's generation process can be view as an arrangement optimization problem that can be resolved by genetic algorithms. In this project, we build a genetic algorithms based photomosaic generation application.

CCS Concepts

 $\begin{array}{lll} \bullet \ Computing & methodologies \rightarrow Machine & learning \rightarrow Machine \\ learning & approaches \rightarrow Bio\text{-inspired} & approaches \rightarrow Genetic \\ algorithms & \bullet \ Applied \ computing \rightarrow Arts \ and \ humanities \rightarrow Fine \\ arts. \end{array}$

Keywords

Genetic algorithms, Photomosaic

1. INTRODUCTION

Photomosaic, a combination of photo and mosaic, is an image that has been divided into tiles, each of which is replaced with another image that matches the target image. When viewed as a whole, it appears to be one image, when in fact the image is made up of hundreds or even thousands of smaller images [1].

Since the process of photomosaic generation includes selecting a set of replacement images and arranging them to match the target image, it just likes a task which trying to find the best distribution of limited resources. Evolutionary computing is suitable for such an optimization problem and in this project we apply genetic algorithms to photomosaic generation.

2. RELATED WORK

In usual, there are two kinds of approaches to generate photomosaic depending on how matching is done.

In the simpler kind, both each tile of the target image and each replacement images are averaged to a single color. Each tile of the target image is replaced with one of the replacement images with the most similar color.

In the more advanced kind, the matching is done pixel-by-pixel rather than downsampled color, by comparing each pixel in the tile of the target image to the corresponding pixel in each replacement images. Each tile of the target image is replaced with one of the replacement images with minimal total difference.

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Both approaches do not limit the number of copies of replacement images, this may make photomosaic monotonous since the sections with the same color in the target image may covered by only a few kind of dominant replacement images.

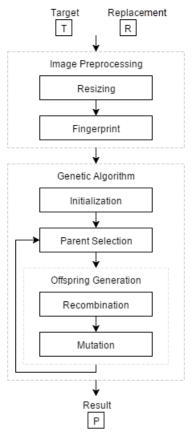


Figure 1. The flow chart of photomosaic generation.

3. PROPOSED APPLICATION

This photomosaic generation application is a MATLAB project. Figure 1 shows the flow chart of the whole procedure, which contains two main parts: image preprocessing and genetic algorithm. Notice that there are some constraints for current version of the application: the same-sized target image and replacement images, the target image is divided into rectangular tiles.

3.1 Image Preprocessing

3.1.1 Resizing

Since the source target image and replacement images are the same size, they must be resized before tiling and matching. There are two kinds of resizing schemes. In Figure 2(a), the target image is scaled up to the same size as tiles of original-sized replacement images. In Figure 2(b), the replacement images are scaled down to fill the original-sized target image. The former generates less resolution issues, but it is more time-consuming when matching images due to the larger number of pixels. Here the later scheme is applied.

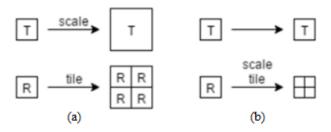


Figure 2. Two kinds of resizing schemes where T represents the target image and R represents the replacement images.

3.1.2 Fingerprint

Like downsampled color mentioned in the related work section, a simple but descriptive image representation can make the image comparison process faster. Approaches such as perceptual hash (pHash) [2], histogram of oriented gradient (HOG) [3], scale-invariant feature transform (SIFT) [4], can be used to generate the image feature descriptors.

3.2 Genetic Algorithms

Table 1 shows the parameters of genetic algorithms for photomosaic generation. Some details are described in the following subsections.

3.2.1 Initialization

For the purpose of minimizing duplicates of replacement images, we use random permutation to arrange the replacement images. If the number of replacement images is smaller than the number of tiles of the target image, another random permutation sequence will be generated and appended to the previous one until all tiles of the target image are full.

3.2.2 Parent Selection

Tournament selection, with summation of Pearson correlation coefficient for each color of the target image and the photomosaic as fitness function, is applied. For gray scale images, fitness function is $\rho_{X,Y}$. For color images, it is $\sum_{r,g,b} \rho_{X,Y}$ where

$$\rho_{X,Y} = \frac{E[XY] - E[X]E[Y]}{\sqrt{E[X^2] - E[X]^2} \sqrt{E[Y^2] - E[Y]^2}}$$

3.2.3 Offspring Generation

3.2.3.1 Recombination Uniform crossover is applied.

3.2.3.2 Mutation No mutation is applied.

4. RESULTS AND EVALUATION

Table 2 shows some results generated by the application. We can measure the effectiveness in terms of similarity to the target image [5] and the costs in terms of number of generations. The evaluation for results in Table 2 are summarized in Table 3.

The similarity in term of fitness function value may be different from the similarity in term of visual perception. This implies that the correlation coefficient fitness function is not deterministic for the quality of photomosaic.

The number of generations is proportional to the size of individual genotype as expected. The running time is generally much more than the ordinary approaches.

Table 3. Evaluation summary of results in Table 2.

		Smaller Tiles	Larger Tiles	
ct	Size of Tiles	<		
Fact	Number of Tiles	>		
uo	Similarity (Fitness)	<		
Evaluation	Similarity (Visual)	> or <		
Ev	Number of Generations	>	>	

5. CONCLUSIONS AND FUTURE WORK

The quality of current outputs of gray scale images is acceptable, but the quality of color images is not since the lack of color in replacement images has larger influence on it. This may be fixed by selecting replacement images according to the portion of colors of the target image, where the initialization of genetic algorithm should be designed carefully to avoid recommitting the same disadvantage of the two ordinary photomosaic generation methods. Besides, more efforts can be made on the fingerprint in image preprocessing and parent selection in genetic algorithm.

6. REFERENCES

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 ${\bf Table~1.~The~parameters~of~genetic~algorithms~for~~photomosaic~generation.}$

Representation	1-dimension array, size: number of tiles of the target image, value: integer id of replacement images
Recombination	Uniform crossover
Recombination Probability	50% for each tile of the target image
Mutation	None
Mutation Probability	0
Parent Selection	Tournament selection
Fitness Function	summation of Pearson correlation coefficient for each color of the target image and the photomosaic
Survival Selection	Generational
Population Size	200
Number of Offspring	1
Initialization	(Repeated) random permutation

Table 2.1. Results of proposed photomosaic generation application.

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512×512-Pixel Target Image		Photomosaic	Fitness Value vs. Generation	
	10×10-Pixel Tiles		Genetic Algorithm for Photomosatic 0.45	
	12×12-Pixel Tiles		Genetic Algorithm for Photomosatic 0.5 0.5 0.1 0.1 0.1 0.5 0.1 0.1	
	15×15-Pixel Tiles		Genetic Algorithm for Photomosatic 0.5 0.5 0.7 0.7 0.7 0.7 0.7 0.7	

Table 2.2. Results of proposed photomosaic generation application.

512×512-Pixel Target Image		Photomosaic	Fitness Value vs. Generation
	10×10-Pixel Tiles		Genetic Algorithm for Photomosatic 0.45 0.45 0.35 0.3 0.35 0.3 0.35 0.3 0.35 0.3 0.3
	12×12-Pixel Tiles		0.45 Genetic Algorithm for Photomosatic 0.45 0.45 0.45 0.45 0.35 0.25 0.25 0.25 0.100 150 200 250 300 Generation
	15×15-Pixel Tiles		0.5 Genetic Algorithm for Photomosatic 0.45 0.45 0.45 0.5 0.5 0.5 0.5

Table 2.3. Results of proposed photomosaic generation application.

1280×720-Pixel Target Image		Photomosaic	Fitness Value vs. Generation
	10×10-Pixel Tiles		Genetic Algorithm for Photomosatic 1.2 1.2 1.2 0.8 0.8 0.6 0.9 0.0 50 100 150 200 250 300 350 400 Generation
株里 西田南湖的南 安	15×15-Pixel Tiles		Genetic Algorithm for Photomosatic 1.5 Genetic Algorithm for Photomosatic
	20×20-Pixel Tiles		Genetic Algorithm for Photomosatic 1.4 1.2 80 1.4 1.2 80 1.4 1.2 80 1.4 1.2 80 1.4 1.2 80 1.4 1.2 80 1.4 1.2 80 1.4 1.2 80 80 80 80 80 80 80 80 80 8