Restoration of Archaeological Artifacts by a Genetic Algorithm with Image Features

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Keywords: Genetic Algorithm, Hill-climbing Algorithm, Three-Dimensional Rebuilding, Image Features.

Abstract: Archaeological artifacts have been discovered all over the world. The restoration work of archaeological artifacts broken into pieces contains positioning problems. Therefore, an intelligent computer-assisted system was proposed to rebuild archaeological discoveries from fragments. A real coded genetic algorithm (GA) and a hill-climbing algorithm was evaluated to reconstruct a 3D object. The fitness function value for the GA was computed from image features of the object. The ORB (Oriented FAST and Rotated BRIEF) technique was used for solving the positional problem by the GA. The proposed method based on the GA with the image features was able to efficiently regulate the 3D surfaces. In further researches, the proposed method for 3D rebuilding could be applied to various practical applications.

1 INTRODUCTION

Archaeological artifacts have been discovered all over the world. Because the discovered artifacts are usually broken into some pieces, it takes a lot of hours to rebuild them from fragments (Halíř, 1999). Furthermore, the archaeological rebuilding is interrupted when pieces are missing or damaged. Archaeologists or experts must evaluate numerous possible combinations under such situations, based on their knowledge and experience.

Efficient methods for the virtual 3D visualization (Scopigno, 2011) have been reported to make digital archives, which could assist the restoration work. Previous computer systems mainly focus on the reconstruction of 3D objects with symmetric patterns, comparing the broken surface boundary curves (Sağiroğlu and Erçil, 2006). Such restoration work needs computing complicated patterns and geometric images by using well-defined mathematical models. However, the 3D rebuilding cannot be completed when the precise mathematical models do not exist.

Intelligent computer systems may be able to address this issue. An easier method for piecing together archaeological objects without using a mathematical model for surface curve fitting has not been established. Here, genetic algorithms (GAs) are one optimization method of positional regulation including the evaluation of countless combinations (Ray and Mahajan, 2002).

Instead of the complicated mathematical model, the image features of 3D objects may be effective for the GA process. SIFT - Scale Invariant Feature Transform (Lowe, 1999) and SURF - Speeded-Up Robust Features (Bay et al., 2008) are well known as basic techniques for image feature detection. More recently, the ORB - Oriented FAST and Rotated BRIEF (Rublee et al., 2011) technique also shows accurate performance, compared with the traditional methods; it is based on the FAST keypoint detector and the BRIEF descriptor. In addition, after a global solution was computed from the GA, hill-climbing methods to find a localized solution may be able to fine-tune the 3D positions.

The purpose of this study was to investigate effective methods for 3D reconstruction of artifacts from fragments, so that the archaeologists can shorten their working time. The proposed method based on GA with a hill-climbing algorithm was evaluated by using image features of a 3D object without mathematical surface or border models. The ORB technique was used for solving the positional problem by the GA because it would be an efficient method to search for similar image patterns.

Kashihara K..
Restoration of Archaeological Artifacts by a Genetic Algorithm with Image Features.
DOI: 10.5220/0004920106910695
In *Proceedings of the 6th International Conference on Agents and Artificial Intelligence* (ICAART-2014), pages 691-695
ISBN: 978-989-758-015-4

2 PROPOSED METHODS

The computer system was proposed to estimate the correct positioning of archaeological fragments (Open GL; Open CV ver. 2.4; Microsoft Visual C++ 2012). For this system, GA computation can find a global solution from numerous combinations of 3D fragments. Fine-tuning is then performed by the hill-climbing method. The 3D reconstruction is based on the silhouettes of an object from some camera angles in order to determine a correct match among fragments. After the GA process, one of nine operations in a target 3D fragment (rotations and parallel movements in each axis) is selected during the hill-climbing method.

2.1 Real Coded Genetic Algorithm

The real coded GA approach was applied to predict the spatial positions of some pieces of a 3D object: angles and coordinate *x*, *y*, and *z* axes. The 3D object is formed by the polygonal meshes of fragments. The GA process consists of the following operations.

(a) The initial population of individuals is randomly generated within a set range. Each individual is shown by real numbers; its score is calculated from a fitness function. The fitness function value is calculated by comparing the current image results at some viewpoints with the correct patterns. The best fitness value is maintained to define the next generation.
(b) A selection operation chooses the individuals for the generation of offspring, and tournament selection is used for the choice of individuals.
(c) A crossover operation combines two individuals to generate an offspring. A blend crossover (BLX-α) operator (Eshelman and Schaffer, 1993) was selected for this study.
(d) A mutation operator randomly changes some individuals, altering the variables of a selected individual to facilitate the diversity in the population. The mutation can avoid falling into a local solution.

The above GA operators are repeated to update the population and create the next generations, modifying the fitness of the population. The GA process stopped after creating some generations.

2.2 Hill-climbing Method

The hill-climbing method was performed to fine tune the positioning after the search spaces have been reduced by the initial GA operation. This method is a traditional optimization technique to maximize a fitness function value. The proposed system is composed of the following steps.

(a) Set the initial points of fragments in a search space. These values are determined by the final results of the GA process.
(b) Compute the fitness function values for all neighbours based on the current state, changing each parameter of the angles and positions of the target fragment.
(c) Choose the neighbour with the best quality indicating the largest fitness value and move to the state.
(d) Repeat the steps (b) and (c) until all the neighbours become no change or lower quality in the fitness values. Change the target fragment to the next one.

2.3 Fitness Function

The similarity of image features of a 3D object from six viewpoints was evaluated to determine the correct positions of fragments. This similarity was the fitness function in the GA and hill-climbing methods, meaning the accuracy of 3D rebuilding. A normalized correlation coefficient (i.e., the similarity between an original image *A* and an evaluated image *B*) is denoted as:

$$r = \frac{\sum_{i=0}^{N}(A_i - \overline{A})(B_i - \overline{B})}{\sum_{i=0}^{N}(A_i - \overline{A})^2 \sum_{i=0}^{N}(B_i - \overline{B})^2}$$
$$\overline{A} = \frac{1}{N}\sum_{i=0}^{N} A_i, \quad \overline{B} = \frac{1}{N}\sum_{i=0}^{N} B_i \tag{1}$$

A_i and B_i are the brightness in each pixel and N is the total number of pixels. $\bar{A}$ and $\bar{B}$ show the mean value of the brightness in each image. The correlation coefficient of Eq. (1) approaches 1 when the similarity increases.

The fitness function is the summation of similarities computed from six camera angles. Additionally, the image feature points were calculated by the ORB technique. If image feature points of two images are the same, the slope value between the feature points will result in zero (Fig. 1A). Therefore, this slope value was added to the fitness function for the GA.

A. Matched case

B. Not matched case

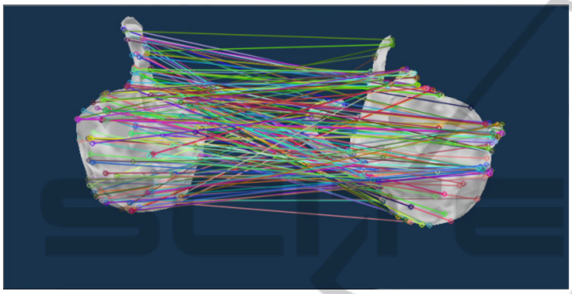


Figure 1: Examples of image features acquired from the ORB technique. The lines between the two objects indicate the corresponding relationship between the extracted feature points.

3 SIMULATION STUDY

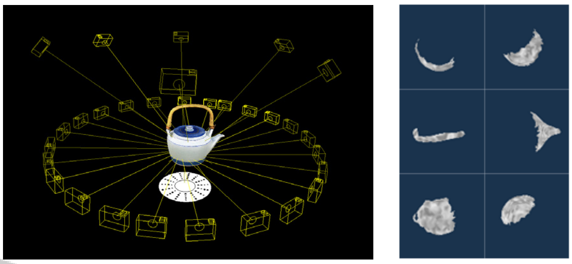
The proposed method was assessed by using a 3D model with asymmetric shapes digitized from an actual object. The 3D reconstruction was performed by the following steps: (1) Create correct patterns using various camera angles; (2) Carry out GA computation for a localized solution. The fitness value of the GA was calculated from the image features obtained from the ORB technique; (3) Regulate 3D positions by the hill-climbing method.

3.1 Evaluation Method

3.1.1 3D Remodeling

To make a digitized 3D object with fragments, photographs were taken from thirty camera locations around the object with a calibration mat (Fig. 2A), every 15 degrees at low angles (24 points) and every 60 degrees at high angles (6 points). After the masking process was applied for the backgrounds of acquired images, the 3D object with 6,000 triangle polygons was created by fixing the position and spatial relationship on the calibration mats of all the images (STRATA FOTO 3D CX2). The 3D model was output in the VRML 2.0 format to estimate the optimal fitting and was divided into 7 fragments (Metasequoia ver. 2.4).

A. Camera angles and fragments



B. Silhouettes of a 3D object

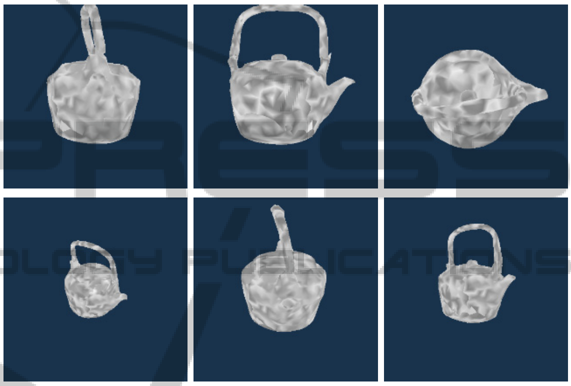


Figure 2: A. Thirty camera angles with a calibration mat to construct a 3D object (*left*). Examples of 3D fragments formed by polygonal meshes with triangles (*right*). B. Correct images from various camera angles.

3.1.2 Parameter Setting

The real coded GA parameters were prepared as follows. The initial population of 30 chromosomes was randomly generated. The probabilities of crossover and mutation were set at 0.50 (BLX-α = 0.40) and 0.01, respectively. The number of iterations in the GA computation was 100 generations.

For the hill-climbing search, step sizes of a fragment were three degrees in rotation angles and 0.002 in parallel movements to each axis of a 3D coordinate. The initial values were based on the result of the GA process. The searching space was limited within the voxel size of an actual object in parallel movement to each axis with free rotations. The maximum number of iterations was set at 200.

As the first fitness function value, the correlation coefficient between the correct and evaluated images (24-bit grayscale; 400 × 400 pixels) was calculated from Eq. (1). The correct images were acquired from the six viewpoints for a 3D object (Fig. 2B). In addition, the image features extracted from the ORB technique were output as bitmap images; the image feature similarities were then computed as the fitness value for the GA.

3.2 Results

Figure 3 shows the change of fitness values for the GA process. The fitness function values gradually increased and the maximum value (r = 3.15) of all generations was obtained during the later iterations. The ORB technique to extract the descriptor as an image feature was also applied to the correct image patterns to compute the fitness function value.

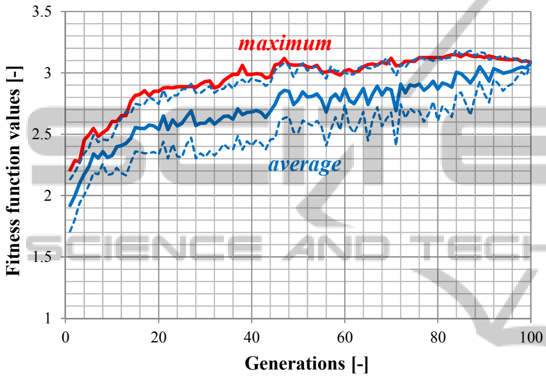


Figure 3: Simulation results of the GA process. A blue line: average fitness values; dotted lines: standard deviations in each generation; a red line: the maximum fitness values.

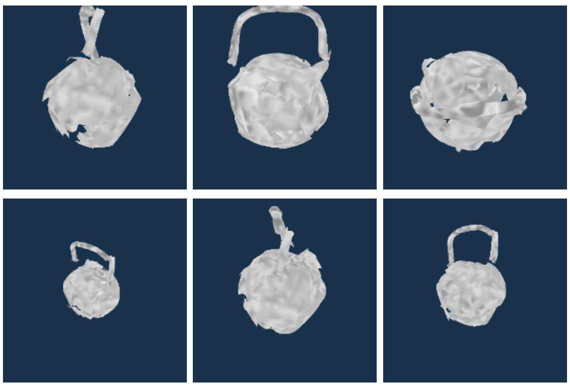


Figure 4: Final simulation results of the GA and hill-climbing methods (six camera angles).

The optimal regulation of fragments was roughly completed by the GA. The fine-tuning was then performed by using the hill-climbing method, which allowed borders of curved surfaces to be smoothly connected (Fig. 4). This result suggests the positive effect of this method began with the initial values determined by the GA process.

4 DISCUSSION

Previous researches for the rebuilding of archaeological artifacts needed well-defined mathematical or rule-based models for the surface curve fitting of broken parts (Halíř, 1999). On the other hand, the proposed method based on the silhouettes of a 3D object can be used for nonlinear and non-continuous surface curves without mathematical models. In addition, the ORB technique was able to fine-tune 3D positions because it can be robust for searching similar images with various rotations and scales.

Although an evaluation with texture mapping was not applied to this research, the distribution of curvatures and drawing patterns of surfaces with colours may be efficient for 3D rebuilding (Sağiroğlu and Erçil, 2006). It is also crucial to prepare a 3D database for a supervised image with correct or similar patterns because it determines the accuracy of reconstruction.

As a user interface for the design drawing of a 3D object, the results of reconstruction could be interactively modified to fine-tune the final positioning of pieces. Actually, there exist optimal visual angles with some perspectives to recognize 3D shapes as quickly as possible (Kashihara and Nakahara, 2011; Kashihara, 2011). Therefore, this result could be applicable to the user interface and drawing design for the manual adjustment of a reconstructed 3D object. The manually adjusted values could be also used as the initial values for the proposed algorithms to acquire the higher accuracy of 3D rebuilding.

5 CONCLUSIONS

The intelligent computer system for reconstructing archaeological artifacts with broken surfaces was designed to assist archaeologists and to reduce unnecessary manual operation. The GA with the hill-climbing algorithm was optimal for determining the best positions of fragments in a 3D object. Furthermore, the ORB technique which can extract the image features of an object was suitable for the fitness function of the GA. In future studies, the proposed method should be applied to practical applications, improving the searching time and user interface. In addition to the virtual repairing of archaeological finds, the proposed system could be available for restoration work on personal possessions such as mementos.

ACKNOWLEDGEMENTS

This study was funded by a Grant-in-Aid for the Okawa Foundation for Information and Telecommunications.

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