Using Particle Swarm Large-scale Optimization to Improve Sampling-based Image Matting*

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ABSTRACT

Sampling-based image matting is an important basic operator of image processing. The matting results are depended on the quality of sample selection. The sample selection produces a pair of samples for each pixel to detect whether the pixel is in the foreground of an image. Therefore, how to optimize the production is usually modeled as a large-scale optimization problem. In this study, particle swarm optimization is applied to solve the problem because its property of rapid convergence is positive to the real-time demand of image matting. We regard every two dimensions of a particle as a sample pair for a undetermined pixel. The encoding can make image matting more effective when there are relevant pixels in the image. The experimental result indicates that the proposed particle swarm optimization performs better than existing optimization method for image matting.

Categories and Subject Descriptors

I.4 [**Image Processing and Computer Vision**]: Applications; G.1.6 [**Optimization**]: Global optimization

Keywords

Sampling-based Image Matting; Sample Selection; Particle Swarm Optimization.

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1. INTRODUCTION

Image matting is to extract the smooth-and-exact foreground object from an image. It was first proposed by movie editing [5], and became a foundation of image processing. The improvement of the matting quality is one of the most important topics in image processing.

The studies of image matting mainly include propagation-based and sampling-based methods. Propagation-based matting methods [1, 3, 17] assume that neighboring pixels are correlated under some image statistics and use their affinities to propagate alpha values [15] of known regions toward unknown ones. Sampling-based methods [6, 7, 12, 19] collect a set of known foreground and background samples and find the best foreground and background samples to estimate alpha value for every undetermined pixel. Therefore, the quality of their matting is depended on the selection of samples. Several methods [6, 19] were proposed to evaluate the samples for the selection. Furthermore, researchers used local sampling and global sampling to establish the sample set. Local sampling methods [6, 19] are to collect samples from a local known region of every undetermined pixel. It was proved to be a fast technique. However, the quality of image matting degrades when the best foreground-background sample pair is not in the sample set. In order to avoid missing the best sample pair, a global sampling method [7] is proposed to collect all known boundary samples. It finds best foreground-background sample pair for every undetermined pixel by solving a global optimization problem. However, the size of the candidate sample pairs is huge so that the time complexity of searching best sample pair for every undetermined pixel is high.

As a result, the sample selection of global sampling (the sample selection for brief) can be modeled as a large-scale optimization problem. It was solved by random search algorithm [2] to produce the best sample pair for alpha evaluation. The result [7] was proved to be better than local sampling methods [6, 19], but not robust enough for the property of random searching. In this paper, we propose a search strategy of particle swarm optimization (PSO) to improve sample selection for image matting. PSO was proved to be a rapid algorithm for optimization with global and local heuristic information [16]. Therefore, we choose it to solve the large-scale optimization problem to improve the sampling-based image matting.

2. OPTIMIZATION PROBLEM OF SAMPLE SELECTION FOR IMAGE MATTING

Image matting is implemented with a trimap image [18], which divides the image into three regions of foreground pixels, background pixels and undetermined pixels, respectively. The trimap can be drawn by the user or generated automatically [18] or semi-automatically [9]. Image matting is to determine whether the undetermined pixel is foreground or background. The process is modeled to be linear combination of the pixel's color shown by Expression (1). For the k^{th} undetermined pixel,

$$I_k = \alpha_k F_k + (1 - \alpha_k) B_k \quad (1)$$

I_k is the color of the k^{th} undetermined pixel, it can be obtained directly from the tackled image. F_k and B_k are colors of foreground pixel and background pixel. They are the optimized variables for the k^{th} undetermined pixel and used to calculate the alpha value α_k by Expression (1), where $\alpha_k \in [0, 1]$. The k^{th} undetermined pixel is foreground if $\alpha_k = 1$, it is background if $\alpha_k = 0$. The aim of sample selection is to find best foreground-background pair which is used to calculate the α_k to accurately determine whether I_k is foreground or background. The basic assumption in sampling-based method is that for any unknown pixel, the best foreground-background pair can be sampled from the known regions. Therefore, the research of sampling-based methods focuses primarily on sampling method.

To find the best foreground-background pair in sample set for each undetermined pixel, He etc. [7] proposed an evaluation model for the sample pair (F^i, B^j) value. For the k^{th} undetermined pixel, the model is shown by Expression (2).

$$f_k(F^i, B^j) = \omega f_c(F^i, B^j) + f_s(F^i) + f_s(B^j) \quad (2)$$

Where F^i is the i^{th} foreground pixel in sample set, B^j is the j^{th} background pixel in sample set. The $f_k(F^i, B^j)$ is the evaluation function of the candidate sample pair (F^i, B^j) for k^{th} undetermined pixel, it is based on both color fitness and spatial distance. $f_c(F^i, B^j)$ is the color fitness of (F^i, B^j) for the undetermined pixel. The color of pixel is gray-scale. $f_s(F^i)$ is the spatial distance between F^i and the undetermined pixel. $f_s(B^j)$ is the spatial distance between B^j and the undetermined pixel. The spatial distance is independent from the absolute distance [7]. ω is a weight which trades off the color fitness and spatial distance, where $\omega = 1$ [7]. A smaller value of $f_k(F^i, B^j)$ indicates that the sample pair (F^i, B^j) can better estimate the alpha value of the k^{th} undetermined pixel. Therefore, the optimization problem of sample selection [7] is to find a sample pair (F^i, B^j) with the smallest value of $f_k(F^i, B^j)$ for each undetermined pixel, which is illustrated by Figure 1.

Suppose that we use global sampling method to avoid missing true samples, the typical size of foreground sample set and background sample set is $10^3 \sim 10^4$ for a $600 * 800$ image [7]. Therefore, there exist $10^6 \sim 10^8$ approximately foreground-background sample pairs. If we use brute-force method to estimate all sample pairs for every undetermined pixel, the time complexity is high. Therefore, a rapid heuristic technique is needed to balance the time complexity and quality of sample selection.

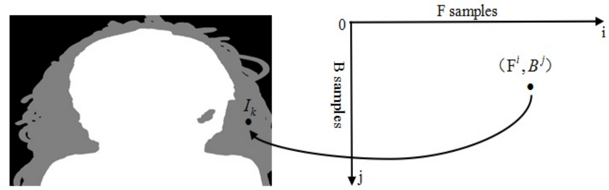

Figure 1: Optimization problem of sample selection. Left: trimap. The black region is background region, the gray region is undetermined region, and the white region is foreground region. I_k is k^{th} undetermined pixel. Right: foreground-background sample pair search space.

3. PARTICLE SWARM OPTIMIZATION FOR SAMPLE SELECTION PROBLEM

3.1 Particle Swarm Optimization

Particle Swarm Optimization(PSO) is a population-based stochastic optimization technique proposed by Kennedy and Eberhart in [4] and [8]. The basic concept of PSO is to simulate the social interaction behavior of birds flocking and fish schooling. PSO is initialized with a swarm of individuals randomly positioned in a multidimensional search space. Each individual of the swarm, called as a particle, flies in the multidimensional search space for looking for the optimal solution.

As PSO is simple in concept and has rapid capability of exploring the global optimal solution. PSO has became one of the most popular optimization techniques and attracted a large number of researchers to study it. The existing researches of PSO can be mainly classified into four categories: tuning the control parameters [13], changing neighborhood typologies [10], hybridizing PSO with auxiliary search techniques [20] and using multiswarm techniques [11].

To improve robust of solving the sample selection problem for sampling-based image matting and simple the implementation of computer code, we first attempt to propose PSO search strategy for sample selection problem. The details of the encoding will be described next.

3.2 The PSO search strategy

In this section, we will describe the formulation of PSO search strategy in detail. One of the key issues in application of PSO is finding a suitable mapping between problem solution and PSO particle. We assume that the number of undetermined pixels is N_u for an input image and a trimap, the size of foreground sample set is N_F, and the size of background sample set is N_B. We sort all the foreground samples F by color, and denote them as an ordered set $S_F = \{F^i | i = 1, 2, 3, ..., N_F\}$. The background sample set $S_B = \{B^j | j = 1, 2, 3, ..., N_B\}$ is sorted similarly. It has been proved that there is no difference between the color and other sorting criteria [7]. The purpose of our PSO search strategy is to find best foreground-background sample pair for N_u undetermined pixels. Therefore, in this paper, we set up a search space of $2N_u$ dimensions. We map the linear array of N_u sample pairs into a $2N_u$ dimensions particle, and map N_p solution instances into corresponding N_p particle positions. Each particle of swarm is denoted as $X_m = (x_m^1, x_m^2, ..., x_m^{2N_u})$, $m = 1, 2, 3, ..., N_p$. Each odd dimension of the particle has a set of possible integer values limited to $\{1, 2, 3, ..., N_F\}$. Each even dimension of the particle has a set of possible integer values limited to $\{1, 2, 3, ..., N_B\}$. We regard every two dimensions of a particle as a foreground-background sample pair for the undetermined pixel. Therefore, each particle contains candidate sample pairs for all undetermined pixels. The velocity of particle is denoted as $V_m = (v_m^1, v_m^2, ..., v_m^{2N_u})$. Each dimension of the velocity has the same limit as the dimension of particle. The PSO search strategy starts by generating randomly N_p particles in a search space of $2N_u$ dimensions as the size of the initial swarm of the PSO.

3.3 The evaluation function of PSO search strategy

Each particle of PSO swarm contains candidate sample pairs for all undetermined pixels. Therefore, the evaluation value of each particle indicates the overall quality of current candidate sample pairs. The evaluation function of our PSO search strategy is on a basis of the evaluation model that was proposed in [7]. The evaluation value of the m^{th} particle is calculated by:

$$\varepsilon(X_m) = \sum_{k=1}^{N_u} f_k(x_m^{2k-1}, x_m^{2k}), m = 1, 2, 3, ..., N_p. \quad (3)$$

A smaller $\varepsilon()$ indicates that the overall quality of current candidate sample pairs is higher.

The pseudo-code of PSO search strategy is shown in Algorithm 1. The part of mapping between the sample selection problem solution and PSO particle is in step 1. Y_m is the local-best position of the m^{th} particle. Y is the global-best position of particle swarm.

Algorithm 1 Particle Swarm Optimization Search Strategy

Input: The size of the ordered foreground sample set N_F;
The size of the ordered background sample set N_B;
1: Randomly generate and initialize N_p particles, each with $2N_u$ dimensions(where each odd dimension of the particle is randomly chosen from the set $\{1, 2, 3, ..., N_F\}$, and each even dimension of the particle is randomly chosen form the set $\{1, 2, 3, ..., N_B\}$).
2: Randomly initialize $V_m, m = 1, 2, 3, ..., N_p$.
3: Repeat
4: **for** each particle $m, m = 1, 2, 3, ..., N_p$ **do**
5: **if** $\varepsilon(X_m) < \varepsilon(Y_m)$ **then**
6: $Y_m \leftarrow X_m$;
7: **end if**
8: **if** $\varepsilon(Y_m) < \varepsilon(Y)$ **then**
9: $Y \leftarrow Y_m$;
10: **end if**
11: $V_m^n = \omega V_m^n + C_1\gamma_1(Y_m^n - X_m^n) + C_2\gamma_2(Y^n - X_m^n)$;
12: $X_m^n = X_m^n + V_m^n$, $n = 1, 2, 3, ..., 2N_u$;
13: **end for**
14: Until termination criterion is met;
Output: The global-best position of particle swarm Y;

Figure 2: Visual comparisons of results of image matting. 1^{st} column: Input image. 2^{nd} column: Input trimap. 3^{rd} column: the results of image matting with random search algorithm. 4^{th} column: the results of image matting with PSO search strategy.

4. EXPERIMENTAL RESULTS

This section will present the experiments and results. The present experiment is to prove that when the sample set is too large to use brute-force method to search best sample pairs, our PSO search strategy can find higher quality sample pairs. We compare the results with existing random search algorithm [2], which was used in a global sampling method [7].

For a fair comparison, we replace the sample selection step [7] with our PSO search strategy and keep other steps unchanged. Therefore, the methods only differ in their sample selection steps. We select six images from a benchmark data set [14] as our experimental images. To evaluate the performance of two search strategies, we compare the visual results of image matting and the mean squared error (MSE) which is a quantitative evaluation to measure the quality of image matting. In addition, the parameter settings and the algorithm procedure of our PSO search strategy follow a modified particle swarm optimizer [16], where a new parameter, called inertia weight, was added. For the iteration numbers, the maximum iteration number of our PSO search strategy is 3×10^4; the maximum iteration number of random search algorithm is $O(10N_u log(N_F N_B))$ [7]. For the experiment tools, the methods were implemented in MATLAB programming language on windows.

Fig 2 shows the visual results of image matting on the selected six images of the benchmark data set [14]. We also conducted a quantitative comparisons of the matting results of two strategies by calculating the MSE. The results of MSE is shown in Table 1.

Table 1: Comparison of the Mean Squared Error

NO.	Random Search Algorithm	Our Method
$Image\_01$	0.0070	0.0082
$Image\_02$	0.1002	0.0201
$Image\_03$	0.0158	0.0022
$Image\_04$	0.0102	0.0027
$Image\_05$	0.0157	0.0026
$Image\_06$	0.0573	0.0123

As shown in Fig 2, intuitively, when applying our PSO search strategy to solve the sample selection problem for sampling-based image matting, we can gain higher-quality matting results on last five images, compared with the results of existing random search algorithm. The continuity of the undetermined region in last five images is better than that in the first image. Therefore, there is a strong relevance among the undetermined pixels of last five images. However, our PSO search strategy performs less well on the first image. The distribution of the undetermined region in the first image is more discrete than that in last five images. Therefore, there is a weak relevance among the undetermined pixels of the first image. These findings are understandable because our PSO search strategy can make image matting more effective when the undetermined pixels have a strong relevance. We further compare the results of MSE shown in Table 1. Table 1 shows that the existing random search algorithm has smaller value of MSE on the first image, and our PSO search strategy has smaller value of MSE on other images. A smaller value of MSE indicates that the result of image matting has higher accuracy. Therefore, the results of MSE agree with our above analysis, in which our PSO search strategy can improve the quality of sampling-based image matting when the undetermined pixels of the input image have a strong relevance.

In summary, our purpose of this research is to use the PSO search strategy with the application of heuristic information to improve the quality and robust of sample selection and thereby improve the quality of the sampling-based image matting. The experimental results show that our method can improve the quality of the sampling-based image matting, especially when there is a strong relevance among the undetermined pixels.

5. CONCLUSION

In this paper, we propose a PSO search strategy for solving sample selection problem for sampling-based image matting by searching the best sample pairs for all undetermined pixels. The experimental results show that our method can gain higher-quality image matting results for these images whose undetermined region has a better continuity, compared with existing random search algorithm. These results further suggest that the PSO search strategy can gain higher-quality sample pairs in sample selection step of the sampling-based image matting. Hence, we can draw the following conclusion. When the sample set of sample selection step is too large to use brute-force method to search best sample pairs for all undetermined pixels, the PSO search strategy is more efficient than random search algorithm, especially when the undetermined pixels of the input image have a strong relevance.

6. ACKNOWLEDGMENTS

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