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Application of Transfer Learning to PSO for Similar Image Search

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Abstract: Remote sensing of the earth surface using satellite monitored sensor data is one of the most important methods for global environmental monitoring. For satellite monitored sensor data, MODIS (Moderate Resolution Imaging Spectoradiometer) satellite data is actively used for the remote sensing data. In remote sensing fields, similar image search which extracts local area images from a given global map image is often required. Similar image search is important because physical changes to the earth's surface caused by human or nature can be monitored. However, long calculation time is required for similar image search in MODIS data due to the very large search space. In our previous research, an effective result was yielded using genetic algorithm on the similar image search from the satellite image. Based on this result, we proposed a particle swarm optimization based search method that globally searches for the problem space using particle groups.

Keywords: particle swarm optimization, transfer learning, similar image search, remote sensing

1. INTRODUCTION

Remote sensing of the earth surface using satellite monitored sensor data is one of the most important methods for global environmental monitoring. For satellite monitored sensor data, MODIS (Moderate Resolution Imaging Spectoradiometer) satellite data is actively used for the remote sensing data. Moderate resolution remote sensing allows to quantify landscape and extent, which can be used to monitor changes in land cover and land use for extended periods of time.

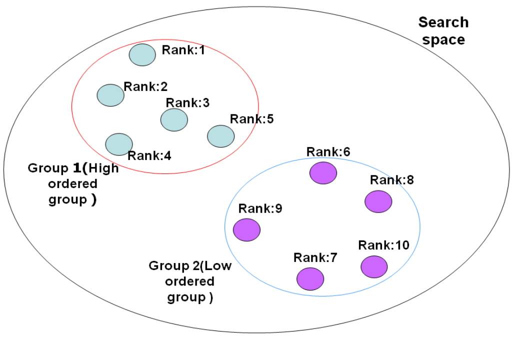
Similar image search is an important problem in the remote sensing using moderate resolution satellite images. Similar image search extracts local area images from a given global image. Similar image search is important because physical changes to the earth's surface are caused by human or nature can be monitored. However, the search space size of the similar image search using MODIS data is very large since MODIS data consists of approximately 1TByte image data per a day. Thus the search process requires long calculation time. In previous research, higher fitness value was yielded using genetic algorithm (GA) on the similar image search from the satellite image. However, the GA depends on improving the solution through a probabilistic learning process, and requires relatively long calculation time. For this result, we proposed a particle swarm optimization (PSO) based method [1] that globally searches for the problem space using particle groups. PSO has advantage in fast conversion rate by comparison with other evolutionary computation algorithm.

Recently, the transfer learning is actively researched [2]. The transfer learning is the meta learning methods that uses the knowledge and data in an domain in order to solve the problem in the another domain. In transfer learning, it is expected that the improvement of the learning efficiency and the compensation for the lack of knowledge and data is performed when the problem is solved. There exists the similarity of pixel data in similar image search. Therefore, more effectively learning can be performed using transfer learning when an image similar to the previous learned image was given. The proposed method can use the learning result for a previous input image in order to learn to another input image. By this characteristic, it is expected that the similar image search is performed effectively. In this paper, we investigated the effectiveness of proposed method.

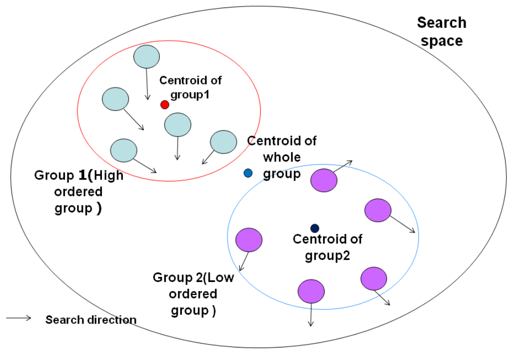
2. METHOD

In PSO [3], a i-th particle is defined by the d-dimensional position vector $\mathbf{x}_i = \{x^1_i, x^2_i, \ldots, x^d_i\}$ and velocity vector $\mathbf{v}_i = \{v^1_i, v^2_i, \ldots, v^d_i\}$ for the d-dimensional search space. A velocity is defined by the local best position $\mathbf{p}_i$ that is own best fitness position at the i-th particle and the global best position $\mathbf{p}_g$ that is best fitness position in the whole particle. Each particle moves according to velocity vector for search.

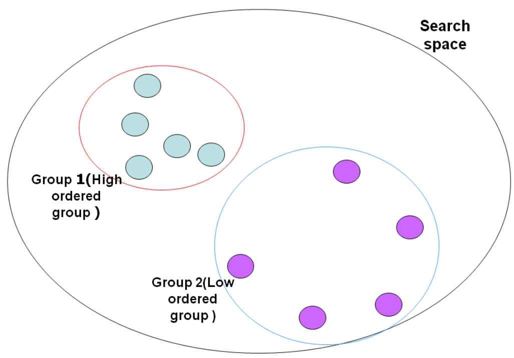
The proposed method divides the particles to the plural groups. Each group is composed of the N/K particles where N is the number of all particles and K is the number of groups. A velocity is defined by the local best position $\mathbf{p}_i$, the global best position $\mathbf{p}_g$, and the group best position $\mathbf{p}_k$ that is best fitness position in a group k. The particles are divided into the group by order of fitness value. Moreover, a velocity is defined to leave from the centroid of each group of the particles and the centroid of all groups of the particles in addition to the local best position, the global best position and the group best position. The particles of high ordered group search in the global best neighborhood and the particles of low ordered group searches around the location to leave for the centroid of each group and the centroid of all groups. In the proposed velocity determination method, the particles of high ordered group fall into local minimum and the particles of low ordered group are searched globally. In addition, the order of each group is changed by the fitness value at generation interval *T*. Behavior of the proposed method is shown in Figure 1 and a flow of the proposed method is shown in Figure 2.



(a) Grouping of the particle by the order



(b) Determination of search direction at every group



(c) Search of every group

Figure 1. Outline of the proposed method

Step1. A position $\mathbf{x}_i$ and a velocity $\mathbf{v}_i$ of each particle are initialized. Each particle is assigned to each group in random.

Step2. A fitness value of each particle is calculated by fitness function $f(\mathbf{x}_i)$.

Step3. The local best position $\mathbf{p}_i$ of the each particle, the global best position $\mathbf{p}_g$ and the group best position $\mathbf{p}_k$ of each group are updated.

Step4. The order $q_i = \{1,2,\ldots,N\}$ is defined by fitness value $f(\mathbf{x}_i)$ to each particle. The particle which got a best fitness value becomes rank 1 and the particle which got a worst fitness value becomes rank N. Each particle has total of the rank value R_i. R_i is calculated by q_i using equation (1)

$$R_i(t+1) = R_i(t) + q_i(t) \quad (1)$$

where t is a generation.

Step5. The position $\mathbf{x}_i$ and the velocity $\mathbf{v}_i$ of each particle are updated by equation (2) and equation (3)

$$\begin{aligned}\mathbf{v}_i(t+1) &= w_k \cdot \mathbf{v}_i(t) + c_1 \cdot \mathbf{r}_1 \cdot (\mathbf{p}_i(t) - \mathbf{x}_i(t)) \\ &+ c_2 \cdot \mathbf{r}_2 \cdot (\mathbf{p}_g(t) - \mathbf{x}_i(t)) + c_3 \cdot \mathbf{r}_3 \cdot (\mathbf{p}_k(t) - \mathbf{x}_i(t)) + h(t)\end{aligned} \quad (2)$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \quad (3)$$

where w_k is momentum rate for group k, $c_1,\ldots,c_5$ is the heaviness for each vector, $\mathbf{r}_1,\ldots,\mathbf{r}_5$ is a vector of random values from 0 to 1 and $h(t)$ is a function that updates the centroid of each group and the centroid of the whole groups. The function $h(t)$ is defined by equation (4)

$$h(t) = c_4 \cdot a(k) \cdot \mathbf{r}_4 \cdot \left\| \mathbf{x}_i(t) - \bar{\mathbf{x}}_k(t) \right\| + c_5 \cdot b(k) \cdot \mathbf{r}_5 \cdot \left\| \mathbf{x}_i(t) - \bar{\mathbf{x}}_g(t) \right\| \quad (4)$$

where $\bar{\mathbf{x}}_k$ is a centroid of group k and $\bar{\mathbf{x}}_g$ is a centroid of whole group. In addition, $a(k)$ and $b(k)$ are values of the functions to increase monotonically in [0,1].

Step6. If a generation is group reordering, go to Step7. If a generation is not group reordering and termination condition is not satisfied, return to Step2.

Step7. Based on total rank of each particle R_i, the affiliation of the particle of each group is changed. For example, the best fitness group is composed of the particles from the rank 1 to rank N/K in the low order of R_i. Each particle is assigned to the low order of R_i in each group. If termination condition is not satisfied, return to Step2.

From this characteristic, the proposed method can use the learning result of a previous input image in order to learn for another input image as transfer learning. Therefore, the proposed method has advantage in the calculation cost reduction and the finding of solution with higher fitness value when another input image is given.

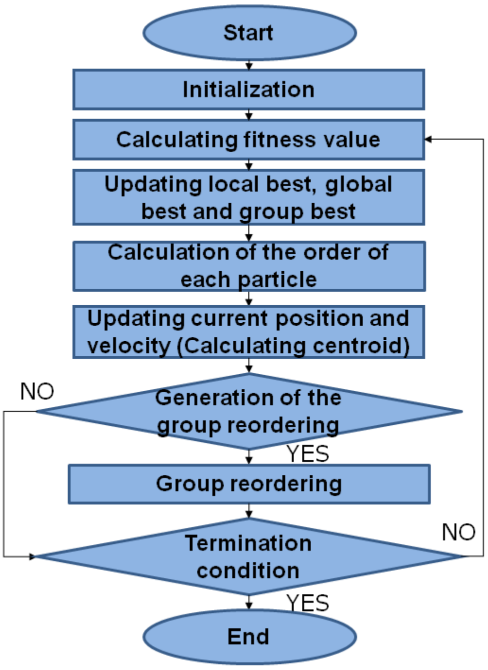


Figure 2. Flow chart of the proposed method

3. EXPERIMENT

3.1 Similar Image Search

A similar image search is a problem that extracts local area images for a given image from global map image. The similar image search is derived by information included in image (ex. a pattern of pixel data and the color). In this experiment, the new input image is given after defining an initial value through the learning of a different satellite image. Therefore, a previous learning result has an influence on the search of a new satellite image. Figure 3 shows a global image, a target image that is new input image, an image1, an image2 and an image3 that are previous input image in this experiment.

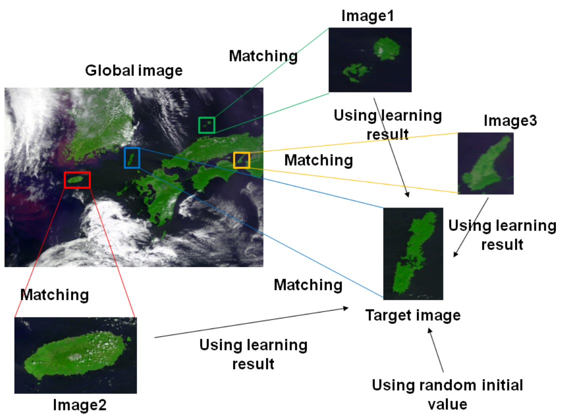


Figure 3. Similar image search in this experiment

In this experiment, the fitness value is calculated by the matching rate of the selected image pixel data specified by the search parameters. The parameters consist of translation, scale rate and rotation angle. The separation (absolute difference) of the values for each color from the compared pixel is calculated, and the sum of the separation is defined as the matching rate for the compared pixel. The fitness value fv is defined by equation (5)

$$fv = 1.0 - \left(\sum_{j}^{y}\sum_{l}^{z}\left|img1_{jl} - img2_{jl}\right|\right) / y \cdot z \cdot 255 \quad (5)$$

where $img1$ is the pixel data for the target MODIS data region, $img2$ is the pixel data for the image data modified by the search parameters and '255' is max value of each color. In addition, each pixel of the RGB color image is converted to gray-scale image using the equation (6)

$$gray = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B \quad (6)$$

where $gray$ is the image pixel of the gray-scale image, R, G and B are the respective red, green, blue pixel data of the color image at the same pixel location, and '0.299', '0.587', '0.114' are a coefficient for each color established in [4].

In this experiment, initial values are set to random value, learning result of image1, learning result of image2, and learning result of image3. Moreover, we evaluated the proposed PSO using the final fitness value of the global best and the conversion rate for the 50 trials. The generation of proposed PSO and GA are set to 500 in each initial value. In addition, the parameters in the proposed method were defined as follows. The number of all particles N is set to 200, the number of groups K is set to 10, the generation interval of the group reordering T is set to 20, the heaviness for each vector $c_1,\ldots,c_5$ are set to 1.5, 1.5, 1.8, 0.9, 0.9, the moment rate for each group w_k is set to from 0.4 to 0.9. GA was used for comparison with this experiment. The parameters in the GA were defined as follows. The population is set to 200, the crossover type is set to 1 point, the crossover rate is set to 0.9, the mutation rate is set to 0.05 and the strategy of selection is set to the roulette strategy and the elite strategy.

3.2 Experiment Result

Table 1 shows the average fitness value of global best position using each initial value in GA and the proposed PSO for target image. Table 1 shows that the proposed PSO yielded the fitness value higher than GA for each condition. Figure 4 shows the fitness value changes in calculation time of GA and proposed PSO when random initial value was used. The proposed PSO yielded the higher fitness value in calculation time less than GA. From this result, the proposed PSO is more effective than GA in similar image search. The search efficiency is improved by this characteristic that the particles of high order group fall into a local minimum and the particles of low ordered group are searched globally. Figure 5 shows that fitness value of a target image using each initial value in proposed PSO. In particular, the higher fitness value is yielded using a learning result of image2 in earlier generation than using random initial value. From this result, a learning result of image2 has a good influence to the search for a new input image. The proposed PSO can perform more effective search by this good influence.

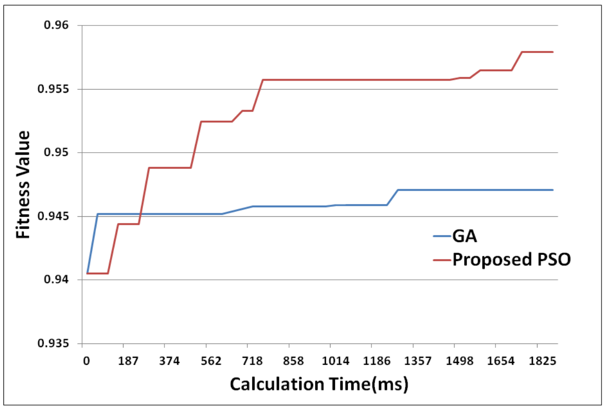


Figure 4. Fitness value changes in calculation time

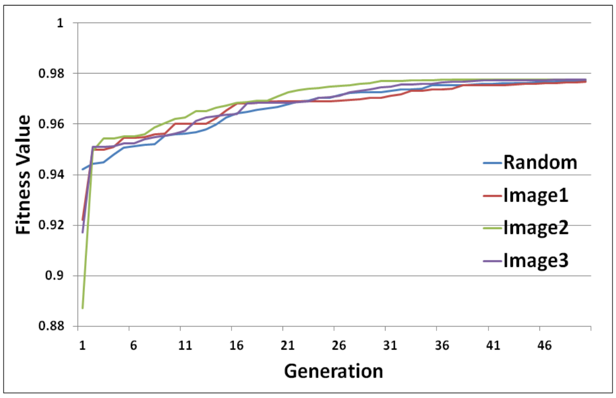


Figure 5. Fitness value of targeted image by each initial value in proposed PSO

Table 1. The average fitness value of global best using each initial value

	Random	Image1	Image2	Image3
GA	0.9609	0.9609	0.9604	0.9601
Proposed PSO	0.9775	0.9775	0.9775	0.9775

4. CONCLUSION

In this research, we proposed the particle swarm optimization based search method that searches for problem space globally by the particle groups and that applies similar image search for investigating the effectiveness of the proposed method. In this experiment, this result showed that the proposed PSO yielded the fitness value is higher than GA. In addition, the proposed PSO yielded the higher fitness value in calculation time less than GA. From this result, the effectiveness of the proposed PSO for similar image search using previous learned image is shown.

In this experiment, we compare the proposed PSO with GA. The distributed genetic algorithm (DGA) that is parallel model of GA has been applied to the similar image search using parallel processing in our previous research [5]. DGA yielded an effective result of calculation time in the similar image search using the parallel processing. For this result, we will plan to implement and evaluate the proposed method using the parallel processing as future works.

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