Cauchy Biogeography-Based Optimization based on lateral inhibition for image matching

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\textbf{A B S T R A C T}

In this paper, a hybrid method of Cauchy Biogeography-Based Optimization (CBBO) and Lateral Inhibition (LI) is proposed to complete the task of complicated image matching. Lateral inhibition mechanism is adopted for image pre-process to make the intensity gradient in the image contrastively strengthened. Biogeography-Based Optimization (BBO) is a bio-inspired algorithm for global optimization which is based on the science of biogeography, searching for the global optimum mainly through two steps: migration and mutation. To promote the optimization performance, an improved version of the BBO method using Cauchy mutation operator is proposed. Cauchy mutation operator enhances the exploration ability of the algorithm and improves the diversity of population. The proposed LI-CBBO method for image matching inherits both the advantages of CBBO and lateral inhibition mechanism. Series of comparative experiments using Particle Swarm Optimization (PSO), LI-PSO, BBO and LI-BBO have been conducted to demonstrate the feasibility and effectiveness of the proposed LI-CBBO.

1. Introduction

Image matching is an area of great importance in the field of image processing as it is a fundamental task for many applications of computer vision such as image registration and image fusion \cite{1}. Many image matching algorithms have been developed \cite{1–4} and they can be classified as image statistics based algorithm or image properties based algorithm \cite{3}. The former algorithm analyzes the attributes of image that reflect the similarity between the template and the original image such as absolute difference, mean absolute difference, square difference, and mean square difference. The later makes use of the image features such as border, unique points, texture, entropy, and energy. The performance of image properties based algorithm depends on the quality and stability of the selected features, which vary in different situations. The image statistics based algorithm makes better performance and widely used as it is independent from extensive feature extractions.

Image matching is a process of searching in the right sub-image in the reference image according to the known template. Image matching algorithm based on image properties has been commonly used to detect interesting objects in complex images under various circumstances. In the matching process, similarity values between the template and all possible positions in the source image have to be computed. Therefore, the time cost can be tremendous \cite{4}. Many global optimization algorithms such as Genetic Algorithm (GA) \cite{5}, Ant Colony Optimization (ACO) \cite{6}, Artificial Bee Colony (ABC) \cite{7}, and Particle Swarm Optimization (PSO) \cite{8} can be applied as the searching strategy to reduce the time cost. In this paper, Cauchy Biogeography-Based Optimization \cite{9} (CBBO) is presented to solve the image matching problem.

BBO is a new algorithm proposed by Simon \cite{9}, which emulates the geographical distribution and the migration of species in an ecosystem. In BBO, every habitat represents a feasible solution. In order to find a solution with the best aspects, the concepts and models of biogeography are applied. The 	extit{Habitat Suitability Index} (HSI) is introduced to measure the goodness of the habitat. BBO works mainly based on two mechanisms: migration and mutation. With the migration mechanism, poor solutions can accept a lot of new features, which may improve the quality of those solutions. Furthermore, solutions do not have the tendency to clump together in similar groups due to its new type of mutation operation in BBO. Elitism operation \cite{10}, which can retain the best solutions in the population from one generation to the next, can also make the BBO algorithm more efficient in both aspects of migration and mutation.

To avoid the potential weakness lying in the basic mutation mechanism of the method, the Cauchy mutation operator is integrated into the standard biogeography based optimization (CBBO) to enhance its exploration ability and to improve the diversity of population.
In this paper, Lateral Inhibition \([11]\) (LI) is introduced into CBBO. The hybrid model is named as Biogeography-Based Optimization based on Lateral Inhibition (LI-BBO). The lateral inhibition mechanism is discovered and verified by Hartline [11] and his research team when they carried out an electrophysiology experiment on the limulus vision. It has been used in the field of image edge extraction, image enhancement, etc. With the lateral inhibition mechanism, the characters of the original image and the position of extracted edge are more stable. Even if variable intensity of illumination changes the gray of the image, the edges can still be extracted effectively with the lateral inhibition. The comparative results show that the proposed method LI-CBBO, which combines the advantages of both CBBO and LI, manifests better performance compared to other bio-inspired algorithms.

The remainder of this paper is organized as follows. Section 2 introduces the principle of CBBO with Cauchy mutation operator and elitism. In addition, the correlation function used in the algorithm is presented in this section. Section 3 proposes the principle of the LI. In section 4, the detailed implementation procedures of the proposed LI-CBBO algorithm for image matching are specified, followed by section 5, a series of comparative experiments are obtained to verify the effectiveness of the proposed approach. The concluding remarks are contained in the final section.

2. Cauchy Biogeography-Based Optimization

2.1. Principles of the BBO algorithm

BBO is an optimization algorithm for multimodal optimization problems inspired by the geographical distribution and the migration of species in an ecosystem. The problem can be of any area in life as long as a qualitative measure of the suitability of a given solution can be obtained [12–17]. In this paper, the BBO technique is applied to the image matching problem.

The BBO algorithm is developed based on the mathematics models of biogeography, which explains how species emigrate and immigrate within the habitats, how new species arise, and how species become extinct. BBO works mainly based on two mechanisms called migration and mutation. In BBO, a set of habitats are used to present the candidate solutions, and Suitability Index Variables (SIVs) are introduced to describe each habitat’s feature. HSI is the evaluation criteria to measure the quality of the solution, analogous to fitness in other population-based optimization algorithms. With migration and mutation mechanisms, the solutions with high HSI tends to share their features with those with low HSI. Thus, poor solutions accept a lot of new features from good solutions. With a habitat \(H\), a vector of SIVs following the migration and mutation steps, the algorithm can eventually reach the optimal solution.

2.2. The migration strategy

BBO migration is a probabilistic operator that adjusts each solution \(H_i\) by sharing features between solutions. In BBO, the migration strategy is similar to the evolutionary strategy in which many parents can contribute to a single offspring [16]. Migration can be expressed as \(H_i(SIV) \rightarrow H_j(SIV)\) [17]. Each individual has its own immigration rate \(\lambda\) and emigration rate \(\mu\), which are related to the number of species on the island. The immigration and emigration rates can be calculated as follows when there are \(S\) species in the habitat:

\[
\begin{align*}
\mu_s &= \frac{ES}{S_{\text{max}}} \\
\lambda_s &= l\left(1 - \frac{S}{S_{\text{max}}}\right)
\end{align*}
\]

where \(E\) is the maximum emigration rate, and \(l\) is the maximum immigration rate, while \(S_{\text{max}}\) is the largest possible number of species that the habitat can support. The immigration and emigration curves are presented in Fig. 1.

The equilibrium species number \(S_0\) is reached when the emigration rate \(\mu\) is equal to the immigration rate \(\lambda\). A linear migration model is illustrated in Fig. 1, but it might be more complicated [18]. Nevertheless, this simple model gives us a general description of the process of immigration and emigration.

Suppose that there are \(N\) habitats, \(H_i\) is one of them, whose immigration rate is \(\lambda_i\), and \(H_j\) is another habitat whose emigration rate is \(\mu_j\). The migration process can be presented in Fig. 2.

The probability \(P_s\), which represents the probability that the habitat contains exactly species \(S\), changes from time \(t\) to time \(t + \Delta t\). It is updated as follows:

\[
P_s(t + \Delta t) = P_s(t)(1 - \lambda_s - \mu_s) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t
\]

2.3. New mutation strategy with Cauchy operator

Mutation strategy can enhance the diversity of the population, which helps to decrease the chances of getting trapped in local optima. On the other hand, elitism is applied to guarantee the survival of the best individual(s) [10]. Solutions with very high HSI and very low HSI have equally lower probability to mutate, while solutions with medium HSI have relatively higher probability to mutate. Mutation is a probabilistic operator that randomly modifies SIV of a solution based on its a priori probability of existence. Species count probabilities \(P_s\) is used to determine mutation rates. Suppose that a habitat with \(S\) species is selected to execute the mutation operation, a chosen variable (SIV) is randomly modified according to its associated probability \(P_s\). The mutation rate \(m(s)\) is given in the following function proportional to \(P_s\):

\[
m(s) = m_{\text{max}}\left(1 - \frac{P_s}{P_{s_{\text{max}}}}\right)
\]

for \(i = 1:N\)

use \(A_i\) to probabilistically decide whether to immigrate to \(H_i\)

if \(A < a_i\) then

for \(j = 1:N\)

select the emigrating island \(H_i\) with probability \(\mu_i\)

if \(A < a_i\) then

\(H_i(SIV) \rightarrow H_i(SIP)\)

end if

end for

end if

End

Fig. 1. The relationship between the number of species and the migration rates.

Fig. 2. The migration process of CBBO.
where $m_{\text{max}}$ is a user-defined parameter, and $P_{\text{max}}$ is the maximum species count probability.

In order to enhance the exploration ability of BBO, a new mutation operator based on Cauchy operator is introduced instead of modifying a selected dimension of the solution vector randomly. The probability density function of Cauchy distribution can be described as follows when the location parameter is 0, and the scale parameter is 1.

$$ f(x; 0, 1) = \frac{1}{\pi (1 + x^2)} $$

(4)

Then, the Cauchy mutation is expressed as follows:

$$ H_j = \min(H_i) + (\max(H_i) - \min(H_i)) \times \pi \times f(H_j; 0, 1) $$

(5)

where $H_j$ is the $j$-th dimension variable of individual $H_i$, and $f(H_j; 0, 1)$ indicates that a Cauchy distributed number is generated for each individual. With this method new individuals are generated in range of $\min(H_i)$ to max($H_i$).

Suppose that habitat $H_i \in \mathbb{R}^N$ represents a feasible solution to some problem, Cauchy mutation process can be presented in Fig. 3.

### 3. Lateral inhibition mechanism

The lateral inhibition mechanism was discovered and verified by Hartline when he carried out an electrophysiology experiment on the limulus’ vision [11] in 1932. Each microphthalthmia of limulus' ommatidium is regarded as a receptor, which is inhibited by its adjacent receptors. The inhibited effect is mutual and spatially summed [19]. The nearer the certain receptors are, the stronger the inhibited effect will be.

In retinal image, the intensively excited receptors in illuminatingly light area inhibit those in illuminatingly dark area more strongly than the latter to the former [20]. Therefore, the contrast and the distortion of sensory information are enhanced. Thus the principle of lateral inhibition can be applied on image processing. In this section, lateral inhibition mechanism is adopted to pre-process both the original and the template images to stress the spatial resolution and increase the accuracy of the image matching.

The following lateral inhibition model is proposed by Hartline and Ratliff with series of electrophysiological experiments [21]:

$$ r_p = c_p + \sum_{j=1}^{n} k_{p,j}(r_j - r_{p,j}), p = 1, 2, ..., n; j = 1, 2, ..., n; j \neq p. $$

(6)

In order to introduce this mechanism to image processing, Eq. (6) is modified to a two-dimensional version as given in Eq. (7).

$$ R(m, n) = I_0(m, n) + \sum_{i=M_{\text{min}}-1}^{M_{\text{max}}-1} \sum_{j=N_{\text{min}}-1}^{N_{\text{max}}-1} \alpha_{ij} I_0(m + i, n + j) $$

(7)

where $\alpha_{ij}$ is the lateral inhibition coefficient of the pixel $(m+i, n+j)$ to the central pixel $(m,n)$. $I_0(m,n)$ is the original gray value of pixel $(m,n)$. $R(x,y)$ is the gray value of pixel $(m,n)$ obtained by lateral inhibition. $M \times N$ is the scale of the receptive field.

In vision nerve system, the relations among one nerve cell to its surrounding nerve cells are relatively stable and consistent, and they are independent to the directions. Therefore, the weight values should be made mutually symmetric according to the center. Suppose that the size of receptive field chosen in this paper is $5 \times 5$, the competing coefficient of the lateral inhibition network is as follows:

$$ R(m, n) = \alpha_0 \times I_0(m, n) $$

$$ \begin{align*}
\alpha_1 & = \sum_{j=1}^{1} \sum_{i=1}^{1} I_0(m + i, n + j) - I_0(m, n) \\
\alpha_2 & = \sum_{j=1}^{2} \sum_{i=1}^{2} I_0(m + i, n + j) - I_0(m, n) \\
\end{align*} $$

(8)

Because the vision nerve cells are situated at the same input plane and the competing coefficients are close to zero, the template of lateral inhibition coefficient satisfies:

$$ \alpha_0 + 8\alpha_1 + 16\alpha_2 = 0 $$

(9)

In this paper, we choose $\alpha_0 = 1$, $\alpha_1 = -0.25$, $\alpha_2 = -0.075$ to form the following matrix as the modulus.

$$ F = \begin{bmatrix}
-0.25 & -0.025 & -0.025 & -0.025 & -0.025 \\
-0.025 & -0.075 & -0.075 & -0.075 & -0.025 \\
-0.025 & -0.075 & 0 & -0.075 & -0.025 \\
-0.025 & -0.075 & -0.075 & -0.075 & -0.025 \\
-0.025 & -0.025 & -0.025 & -0.025 & -0.025 \\
\end{bmatrix} $$

(10)

After combining the modulus template $F$ with Eq. (8), a new gray scale of the image can be obtained. The image’s edge is extracted by the following equation:

$$ B(x,y) = \begin{cases}
255 & R(x,y) \geq T \\
0 & R(x,y) < T
\end{cases} $$

(11)

Where $T$ is a user-defined threshold value, and $R(x,y)$ is the gray value of pixel $(x,y)$ processed by lateral inhibition.

### 4. Hybrid CBBO and lateral inhibition

#### 4.1. The fitness function of LI-CBBO

The fitness function is defined to calculate the HSI for each habitat in different situations of the problems. As analyzed before, gray cross-correlation measurement basing image matching algorithm has strong ability to suppress noise and the performance of simple
calculation. However, it is time-consuming. Therefore, the image matching method presented in Fig. 4 is chosen to calculate the fitness of CBBO and reduce computational load. This method is suitable for the lateral inhibition processed images.

Where $(x_0 + i, y_0 + j)$ and $(i,j)$ are the coordinates of the pixel in the original image and the template respectively. $M \times N$ is the size of the template. $B(x_0 + i, y_0 + j)$ and $b(i,j)$ are the gray value of the pixel $(x_0 + i, y_0 + j)$ and $(i,j)$ respectively processed by equation (11). Suppose that the size of the original image is $P \times Q$, the range of the coordinate in the original image for matching is $0 \leq x < P - M + 1$, $0 \leq y < Q - N + 1$. In BBO, the maximum value fitness stands for the best HSI, correspondingly the habitat is the best solution of the image matching problem.

### 4.2. The procedure of LI-CBBO

LI-CBBO combines the efficiency of CBBO and the accuracy of LI. In this section, LI-CBBO is applied to the template matching problem. The main steps involved in this process are given below:

**Step 1:** Image pre-processing. Obtain the original image and the template image, and convert them into grayscale format. Filter images to remove the noise. Use the lateral inhibition mechanism to pre-process both the original and template images according to equations (8–11) and save the new matrices of images.

**Step 2:** Initialize the CBBO parameters. Derive a method of mapping problem solutions to SILs and habitats, which is problem dependent. Initialize the maximum species count $S_{max}$ and the maximum migration rates $E$ and $I$, the maximum mutation rate $m_{max}$, and an elitism parameter $Keep$. Initialize the step size used for numerical integration of probabilities $dt$.

**Step 3:** Initialize habitats. Randomly initialize a set of habitats with each habitat corresponding to a potential solution.

**Step 4:** Calculate $\lambda$ and $\mu$. For each habitat, map the HSI to the number of species $S$, the immigration rate $\lambda$, and the emigration rate $\mu$, according to equation (1).

**Step 5:** Migrate. Probabilistically use immigration rate $\lambda_i$ and emigration rate $\mu_i$ to modify each non-elite habitat. Re-compute each HSI according to equation (1).

**Step 6:** Mutate. For each habitat, update the probability of its species count according to Eq. (2). Mutate each non-elite habitat based on its probability according to Eqs. (3) and (5), and re-compute each HSI according to section 4.1.

**Step 7:** If the stopping criterion is satisfied, stop the iterations and output the solution, otherwise, go to **Step 4** for the next iteration. This loop can be terminated after a predefined number of iterations, or after an acceptable problem solution has been found.

The detailed flow chart of the proposed LI-CBBO approach for image matching is shown in Fig. 5.

### 5. Comparative experimental results

In order to verify the feasibility and effectiveness of our proposed algorithm LI-CBBO for image matching, we conduct a set of comparative experiments in this section. The methods are programmed using Matlab 2010 and implemented on a PC with 512 MB of RAM under Windows XP operating system. Based on the tests and practical experience, the initial parameters of the LI-BBO method are set as follows. The total population size is decided by the size of the images, the number of generations $N=100$, the step size used for numerical integration of probabilities $dt=1$, the maximum
migration rates $I=1$, $E=1$, the maximum mutation probability $m_{\text{max}}=0.001$, the number of elitisms $keep=3$.

The results of the experiment with the template image ($115 \times 62$) shown in Fig. 6(a) and the original picture ($413 \times 600$) shown in Fig. 6(c) are given.

Template and original images processed by the lateral inhibition are shown in Fig. 6(b) and (d). It is obvious that the edge of the image is enhanced and the detail loss of image is avoided. From the experiment results given in Fig. 6(e), it is clear that the LI-CBBO method can certainly find the location of the template in the original image successfully and accurately. One more complex case is given in Fig. 7 to enhance the function of LI-CBBO optimization.

From the experimental results shown in Fig. 6 and Fig. 7 it is obvious that the spatial resolution of the images can be stressed and the edge information is enhanced as well. The image matching problem is solved effectively with the LI-CBBO algorithm. The results confirm that our proposed method is stable for solving image matching problems in different situations.

Further experiments are given in Fig. 8 and Fig. 9 to verify the stability and advantage of the LI-CBBO. For each case, the algorithm runs for 10 times independently and the evolutionary curves are obtained to test the stability of the proposed algorithm. To prove that the performance of LI-CBBO is better than others, some competitive bio-inspired intelligent methods should be chosen.
Comparative experiments are conducted by using PSO, LI-PSO, BBO, LI-BBO, and LI-CBBO. Different algorithms are presented to match the same template image and original image. For comparison purposes, the fitness values of different methods are normalized. The population sizes and the numbers of iterations of all these algorithms are set to be the same.

In Fig. 8 and Fig. 9, the evolutionary curves of the PSO, LI-PSO, BBO, LI-BBO and LI-CBBO are all presented. Among them, the converging rate of LI-CBBO is the fastest apparently. From the comparative results, it is obvious that the LI-CBBO converges much faster than the other four methods. On the other hand, the BBO converges much faster than PSO. Furthermore, the converging rate and accuracy of our proposed algorithm shows that the LI-BBO method is more reliable than the other three algorithms and it can solve the image matching problems effectively under different environments.

6. Conclusions

This paper develops a hybrid algorithm LI-CBBO to characterize image features and measure the degree of similarity between original image and template efficiently and effectively. BBO is a new simulated biological intelligent algorithm which is of some features that are unique to the biology-based optimization methods. Cauchy mutation strategy is applied to improve the performance in CBBO. Furthermore, LI-CBBO is much better than CBBO as it uses lateral inhibition in the image pre-processing for edge extraction and takes advantages of the accuracy and stability of it. Comparative experimental results using the proposed method, basic PSO, LI-PSO, basic BBO, and LI-BBO algorithms are also given to demonstrate that the proposed LI-CBBO approach is practicable and effective. It may finally be concluded that LI-CBBO is a more effective and robust image matching method.

Our future work will focus on applying this novel technique to more complicated patterns and real-world images in complicated noisy environments, and implement this hybrid approach with embedded processors.

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