An enhancement of ladar image based on SFLA algorithm

Zeng Zhen[1], Lu Lin, Wang Yuanqin

Abstract: Because resulting image of laser radar echo signal is weak, it is necessary to improve the relative gray scale of each point. This article proposed an adaptive image enhancement algorithm based on FSFLA (A Fast Shuffled Frog Leaping Algorithm). This algorithm is based on a fast shuffled frog leaping algorithm with larger scan scope, faster convergence rateandshorter computing time. When the algorithm is applied into ladar image, the effect of image enhancement is faster to achieve compared to tradition SFLA algorithm. As a result, this algorithm is more applicable in actual occasion. Under the condition of 24 given initial value, SFLA needs to convergent 20 times to achieve stability in average while FSFLA only needs 6 times in average, thus greatly improving the computing time.

Keywords: FSFLA algorithm,mean square error function, laser radar, image enhancement

1.1 Introduction

Compared with the infrared and visible light imaging, laser imaging technology has outstanding advantages [1]. The echo signal with rich noise in laser radar imaging system is very weak, illustrated that the gray value of signal pixel is very small and so is the gray level difference, which will lead to a decrease in signal extraction accuracy. So it is necessary to improve the relative gray value of each point in the image without distortion.

According to recent researches, enhancement method includes wavelet technique, fuzzy theory, genetic algorithm [2] and Retinex theory [3] etc. There are a lot of defects

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in practical application, such as the large amount of calculation which is not suitable for real-time image processing, bad intelligence and self-adaption. The genetic algorithm uses the biological evolution and genetic algorithm, which is self-organizing, self-adaptive, intelligent and easily parallelized [4].

Elbeltagi [5] compared execution time, convergence speed and optimization results of 5 kinds of evolutionary algorithms (SFLA, MA, PSO, ACO and GA) in 2005, which showed that SFLA has the highest success rate and the fastest convergence speed when solving the Benchmark function F8 solution. However, due to the small search range of SFLA, the initial population is very huge which leads to its slow convergence speed, large amount of computing time, low operation efficiency and easily falling into local extremum.

To solve theseproblems, this paper designed an enhancement algorithm based on an adaptive image shuffled frog leaping algorithm with greater search range and faster convergence speed, taking the properties and characteristics of laser radar image into account.

1.2 Ladar image enhancement algorithm based on fast shuffled frog leaping algorithm

1.2.1 SFLA algorithm

Grouping strategyisadapted during the Shuffled frog leaping algorithm (SFLA) execution, and multiple sets of local search occur in parallel. The individuals are regrouped to realize the information interaction between different groups andaccelerate the global search after a certain number of executions[6]. The leapfrog step update formula is $\mathrm{D_i} = \mathrm{rand}()(\mathrm{X}_b - \mathrm{X_w})$ and location updateformulais $new\mathrm{X_w} = \mathrm{X_w} + \mathrm{D_i}$, where rand() indicatesa random number between [0,1], $X_b$is the local optimal value of each subgroup, $X_w$is local worst value, D_i indicates the update step.

The main words in all headings (even run-in headings) begin with a capital letter. Articles, conjunctions and prepositions are the only words which should begin with a lower case letter.

1.2.2 FSFLA algorithm

SFLA algorithm does not meet the requirements in practical applications because of its poor convergence speed, low accuracy, easily being trapped in local optimum, random determinant, and lack of theoretical proof [7]. Based on the above issues, this paper proposes a fast shuffled frog leaping algorithm (FSFLA).

Taking one-dimensional quadratic function as an example, threedifferent distribution of local optimal value X_b, local suboptimal values X_s and local worst value$X_w$are shown in Figure 1.1.

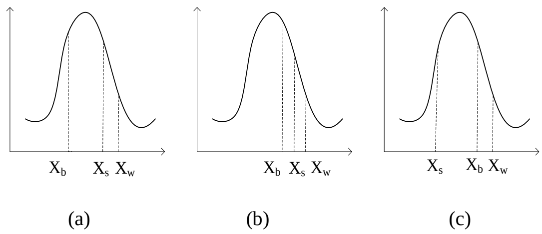


Fig.1.1:Different distribution of local optimal value X_b、 local sub optimal value X_s and local worst value X_w.

Figure 1.1 (a) and (c) showsthat optimal solution locates between$X_b$andX_s. In multi-dimensional case,as the initial value increasing to a certain number, optimal value and sub optimal values either still appear this kind of distribution or locate in different summit,which provides the opportunity to break the local extremum.

Therefore, the individual shouldlearn tonot only local optimal value $X_b$but alsoX_s. Update formula:

$$\mathrm{D_i} = r_1 \cdot \mathrm{rand}()(\mathrm{X}_s - \mathrm{X_w}) + r_2 \cdot \mathrm{rand}()(\mathrm{X}_b - \mathrm{X_w}) \quad (1.1)$$

Wherer1 and r2 arethe weight factors, whose values must satisfy $r_1>0$、 $r_2>0$ and r1 + r1 = 2, depending on different solution.

1.2.3 Demonstration of converges and search capabilities

A Kth iteration update equation can be expressed as:

$$X_w^{k+1} = X_w^k + \alpha\left(X_b^k - X_w^k\right) + \beta\left(X_s^k - X_w^k\right). \quad (1.2)$$

Where the number of real-profile factor alpha and beta can be obtained according to the above formula, the combination of the kth iteration and(k +1)th:

$$\Delta X_w^{k+1} = \left(1 - \alpha - \beta\right)\Delta X_w^k + \alpha \Delta X_b^k + \beta \Delta X_s^k\,. \quad (1.3)$$

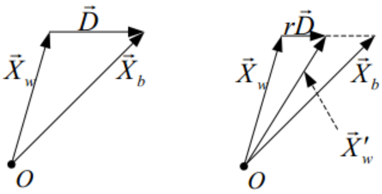
In which $\Delta X_w^{k+1} = X_w^{k+2} - X_w^{k+1}$, $\Delta X_w^k = X_w^{k+1} - X_w^k$, $\Delta X_b^k = X_b^{k+1} - X_b^k$,

$\Delta X_s^k = X_s^{k+1} - X_s^k$.Dividing both sides of ΔX_w^k and according to the triangle inequality theorem:

$$\frac{\left|\Delta X_w^{k+1}\right|}{\left|\Delta X_w^k\right|} \leq \left|1-\alpha-\beta\right| + \alpha \frac{\left|\Delta X_b^k\right|}{\left|\Delta X_w^k\right|} + \beta \frac{\left|\Delta X_s^k\right|}{\left|\Delta X_w^k\right|}. \tag{1.4}$$

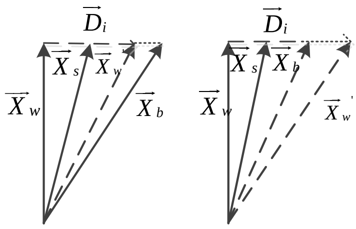
The best individual update step must be less than the worst one, at the same time optimal value update probability is much smaller than the update probability itself, i.e. $\left|\Delta X_b^k\right| \backslash \left|\Delta X_w^k\right|$ <<1 and $\left|\Delta X_h^k\right| \backslash \left|\Delta X_w^k\right|$ <<1, so that the second term can be ignored. As k increases, the updatesteps of the worst individual form a sequence $\left\{\left|\Delta X_w^k\right| \mid k=1,2,\cdots\right\}$ which can be regarded as a geometric series whose common ratio order of magnitude is proportional to |1-α-β|. The searching process is convergent if this sequence is decreasing. In order to ensure the convergence of the search, alpha and beta shouldmeet $\left|1-\alpha-\beta\right|<1(0<\alpha+\beta<2)$. In order to improve the diversity and the randomness of the update process, the acceleration factor alpha and beta are, respectively, set into a random number between 0 and 1, and thus the iterative process of updating policy can be expressed as formula (1.1).

Assuming that vectors $\vec{X}_b$、$\vec{X}_s$和$\vec{X}_w$ represent for optimal, second-best and worst individual values X_b、X_s and X_w, and $\overrightarrow{D_i}$ is the update step, $\vec{X}_w{}'$ is the worst individual values after the update, r is the update factor rand (). Thus the traditional update algorithm of formula can be representedwithFigure 1.2:



(a) r = 1 (b) 0 < r < 1

Fig.1.2:Traditional updating



(a) (b)

Fig.1.3: Updating of FSFLA

Because the update factor r is set to a random number between 0 and 1, $\vec{X}_w'$ can only be located between $\vec{X}_b$ and $\vec{X}_w$, more importantly, $\vec{X}_w'$ is impossibleto exceed $\vec{X}_b$, this limits the search range and is easily confined to the local extremum.That's why the number of initial frog must be increased in SFLA in order to improve the convergence of the algorithm.

The updating formula of FSFLA algorithm can be expressed as shown in Figure 1.3. Figure 1.3(a) showsthat update factors alpha and beta is a random number between 0 and 1, so thatthe update results cover SFLA's search area. Figure 1.3(b) shows that the algorithm can also exceed the value of the best individual, expand the scope of the search and avoid falling into local extremum. That's the reason why FSFLA algorithm can effectively improve the convergence.

1.2.4 Image enhancement based on Beta function and mean square error function

The paper adapted FSFLA algorithm, non-complete Beta function to realize automatic fittingsof gray-scale image enhancement transform curve and the mean square error function as an evaluation function to find out the optimal parameters of the nonlinear transformation function for each image adaptively, in order to achieve adaptive image enhancement.

1.3Experimental results analysis and comparison

This algorithm is carried out under visual studio environment. The original images and the result images after6 iterationsare shown in Figure 1.4, 5,6, (given 24 random initial values with r1 and r2, respectively, 1.9 and 0.1).These six images are wall, trees, grass, vehicle, Figure 1.and building. Because ofnight uneven illumination, there will be stripes in enhancement images.Figure 1.6(b) shows that images taken undersunlightwith small aperture and little exposure time will not have this phenomenon.

Fig. 1.4: The original image

Fig. 1.5: SFLA result

Fig.1.6: FSFLA result

SFLA、FSFLA convergence curve comparison are shown in Figure 1.7：

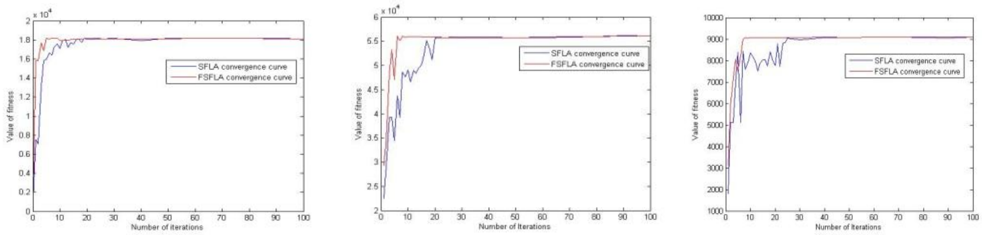


Fig. 1.7 (a) wall**Fig. 1.7**（b）trees**Fig. 1.7**(c) grass

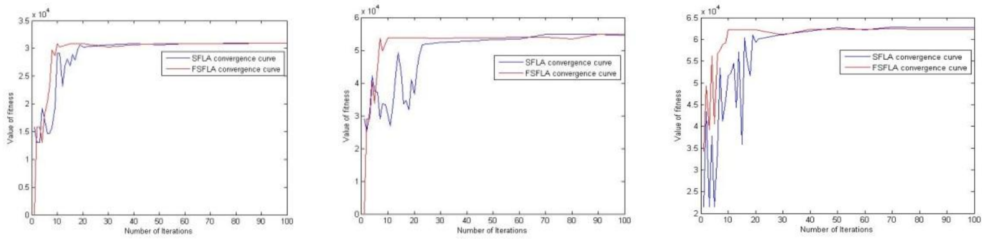


Fig. 1.7(d)vehicle**Fig. 1.7**（e）Figure**Fig. 1.7** (f) building

Fig. 1. 1.7SFLA、FSFLA convergence curve comparison

Table 1.1 Iteration number after convergence comparison

	Wall	Trees	Grass	Vehicle	Figure	Building
SFLA	19	20	23	18	23	19
FSFLA	6	6	7	8	7	6

Figure 1.7 and Table 1.1showthat FSFLA algorithm can achieve convergence faster than SFLA, leading to fasterrunning speedof image enhancement.

1.4 Conclusions

Because of the weak echo signal of lader imaging system, a fast adaptive image enhancement algorithm based on fast shuffled frog leaping algorithm for laser radar images is proposed in this paper. FSFLA expands the searching scope,which will effectively decreasethe runningtime, and is more suitable for real-time applications. The algorithm stretches the gray scales of the target arearather than the entire region. Moreover the gray scalesof the background area are preferably compressed which will lead to a high SNR.

1.5 References

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