Robust visual tracking based on a modified flower pollination algorithm

Yuqi Xiao¹, Yongjun Wu², Fan Yang³
¹ West Anhui University, Lu’an City, 237012, Anhui, China
² School of Traffic and Transportation, Chongqing Jiaotong University, Nan’an District 400074, Chongqing, China
³ Zhuzhou branch, Agricultural Bank of China, Zhuzhou 412000, Hunan, China
Corresponding author: Yuqi Xiao (e-mail: csuxyq@163.com)

ABSTRACT In this study, a target tracking algorithm based on the flower pollination algorithm (FPA) is proposed. This method solves the problem of robust visual target tracking in different complex tracking scenes with the good global and local optimisation ability of the FPA. Meanwhile, with the aim of solving the problem of invalid background feature interference and the loss of effective features caused by the fixed scale of tracking frame in traditional tracking methods, a scale adaptive adjustment model of tracking frame is proposed. Considering that the FPA has good global and local optimization ability at simultaneously, the position update equation of the FPA is introduced as the main optimization method of target tracking. In addition, considering that the traditional FPA is similar to classical swarm intelligence algorithm (such as the particle swarm optimization algorithm), it also faces the problems of a high probability of falling into local extrema, a low efficiency of late convergence speed and a high probability of early maturity. Therefore, this work proposes the GTFPA, an advanced FPA based on the gravitational search algorithm (GSA) and mutation mechanism via a trigonometric function. We qualitatively, quantitatively and statistically compare the proposed method with other classical general tracking methods through two datasets, OTB2015 and VOT2018, which contain hundreds of video sequences and more than ten tracking scenes and can effectively test the success rate, accuracy and stability of the trackers. The results of a large number of tracking experiments in a variety of complex tracking scenarios prove that the proposed GTFPA tracker performs well with regards to efficiency, accuracy and robustness.

INDEX TERMS Computer vision technology; flower pollination algorithm; scale adaptive tracker; generative tracking method

I. INTRODUCTION
Visual target tracking is an important research hotspot in the field of machine vision and has been applied to many cutting-edge technologies, such as vehicle assisted driving, competitive photography, virtual reality and crime prediction [1–3]. The technical difficulties faced by this subject include: 1) complex and changeable tracking scenes, including deformation, occlusion, rotation, motion blur and so on. 2) efficiency, accuracy and robustness. Visual tracking has high research value and many research results in target tracking have emerged [4.6].

A. Related Works
Ref. [7] proposed the efficient convolution operators (ECO) for tracking, which simplified the parameters of the discriminative correlation filter (DCF) by introducing a factorized convolution operator. This method greatly advanced the tracking efficiency. Ref. [8] brought forward the learning continuous convolution operators (C-COT), which proposes a novel formulation for learning a convolution operator in the continuous spatial domain and enables an elegant fusion of multi-resolution feature maps in a joint learning formulation. The C-COT tracker is featured with high accuracy. Ref. [9] presented the multi-store tracker
(MUSTer), a two-component approach consisting of short- and long-term memory storage for processing target visual memory. The MUSTer has a good tracking effect for solving scenes with complex backgrounds. Ref. [10] proposed the unified formulation for discriminative visual tracking (SRDCFdecon), which contains a unified learning formula for training the sample damage problem in tracking the detection paradigm. This method is universal and can be integrated into other discriminant tracking frameworks. Ref. [11] put forward the learning background-aware correlation filters (BACF), a background aware correlation filter based on HOG features, which can effectively simulate how the foreground and background of an object change over time. Ref. [12] proposed the large margin object tracker with circulant feature maps (LMCF), a new tracking approach that absorbs the strong resolution of structured output support vector machine (SVM) and accelerates the tracking speed significantly through correlation filtering. Ref. [13] presented a scale adaptive tracking algorithm based on a correlation filter tracking framework (SAMF). The SAMF performs very well in challenging tracking scenes such as scale variation and deformation. Ref. [14] proposed the discriminative scale space tracker (DSST), a robust scale estimation method based on detection and tracking framework, which is implemented by learning discriminant correlation filters based on the scale pyramid representation. Ref. [15] proposed a particle filter tracker advanced by the mean-shift algorithm (MSPF). The MSPF tracker is suitable for challenging tracking scenes involving fast motion and occlusion. Ref. [16] presented the spatial-temporal regularized correlation filter (DeepSTRCF) that can deal with the boundary effects of hand-crafted features and handle the inefficiency problem of the spatially regularized discriminative correlation filters. Ref. [17] proposed a correlation filter tracker improved by a convolutional operator (SiamVGG). The SiamVGG tracker can track fast-moving and motion blurred visual targets with high precision and efficiency. Ref. [18] put forward the a multi-cue analysis framework for robust visual tracking (MCCT), which combines various features of objects in multiple views and performs well in tracking precision and robustness.

B. Motivation

Most of the above tracking methods are suitable for specific tracking scenarios or they suffer from one or more defects in efficiency, accuracy, robustness, stability and so on. In order to solve the above defects, we identify two main improvement directions for visual tracking methods: search strategy and tracking frame scale adjustment strategy.

1) Search strategy

An effective search strategy is vital for improving the tracking efficiency of a visual target, and the flower pollination algorithm (FPA) has good global and local optimization ability simultaneously [19-22]. Therefore, this study introduces a position update equation of the FPA as the main optimization method of visual target tracking. However, the traditional FPA still faces the problems of a high probability of falling into local extrema, low convergence efficiency and a high risk of premature convergence [23-26]. Therefore, the main task of this study is to propose an improved flower pollination tracking method with high efficiency, high precision, good stability and universality for a variety of complex tracking environments.

2) Scale adjustment strategy of tracking frame

The scale of the tracking frame of the traditional visual target tracker is fixed in the whole tracking process [27-28]. On this basis, it cannot adapt to the change of target scale, and can easily mix too many invalid features or lose some effective features, which affects the accuracy and efficiency of the tracking process [29-31]. Therefore, it is essential to study and propose a model in which the scale of the tracking frame can be adjusted adaptively with the actual situation of the target.

C. Contribution

The main research innovations and contributions of this work are as follows:

1) A scale adaptive adjustment model of the tracking frame is established. The proposed model allows the tracking frame to adequately adapt to the change of target scale and reduces invalid background features and improve the proportion of effective features.

2) A robust visual tracking algorithm based on the FPA is proposed. An improved FPA algorithm based on the gravitational search algorithm (GCA) and mutation mechanism via a trigonometric function (GTFPA) is proposed. This new method helps solve the common problems of the standard FPA, including the high probability of falling into
local extrema, low convergence efficiency in the later stage of iteration and sample degradation. Thus, the efficiency and accuracy of the target tracking process based on the FPA are greatly optimized.

3) The dynamic adjustment mechanism of the conversion probability of the FPA algorithm is established. In this study, a conversion probability adjustment mechanism based on an exponential function is proposed, so that the conversion probability decreases dynamically with the iteration of the algorithm. This mechanism not only ensures that the FPA tracker can fully explore the search space in the early stages and increase the accuracy of the global optimal value, but also ensures that the algorithm can accelerate the convergence speed in the later stage of iteration.

Through the comparison of qualitative, quantitative and statistical experiments on OTB2015 and VOT2018, it can be seen that the newly proposed GTFPA tracking algorithm performs well in efficiency, accuracy and robustness, and the visual tracking results under eight typical tracking scenarios show that the tracking frame of GTFPA algorithm can always closely fit the tracked object and has good tracking accuracy and stability.

II. THEORETICAL MODEL OF TARGET TRACKING

A. MATHEMATICAL MODEL OF TARGET STATE

The mathematical model of the target state is as follows:

\[
\begin{align*}
    f_{t-1} &= \left[ f_{t-1}^x, f_{t-1}^y \right] \in \mathcal{N}(0, Q) \\
    Q &= \text{diag}(\sigma_1^2, \sigma_2^2)
\end{align*}
\]  

(2)

The target observation equation is as follows:

\[
\begin{align*}
    Y &= h(X_i) + \nu_i \\
    h(X_i) &= \left[ r_i, \theta_i \right]^T \\
    r_i &= \sqrt{x_i^2 + y_i^2} \\
    \theta_i &= \arctan\left(\frac{y_i}{x_i}\right)
\end{align*}
\]

where \( r_i \) represents the distance coordinates, \( \theta_i \) represents the phase coordinates and \( \nu_i \) refers to the Gaussian white noise similar to \( f_i \).

B. MATHEMATICAL MODEL OF TARGET APPEARANCE

The appearance model of a certain image area \( j \) is represented by the characteristic probability density function of this area, which is expressed as follows:

\[
\begin{align*}
    p(X_j) &= C \sum_{i=1}^{N} k \left( \frac{X_i - X_j}{r} \right)^2 \delta[b(X_i) - u] \\
    k(x) &= \frac{3}{4} (1 - x^2) \\
    C &= \frac{1}{\sum_{i=1}^{N} \left( \frac{X_i - X_j}{r} \right)^2}
\end{align*}
\]

(4)

where \( X_j \) represents the motion state coordinates of target \( j \) in the desired image area, \( X_i \) refers to the motion state coordinates of the \( i \)-th image area of the current frame, \( \delta[\cdot] \) is the delta function, \( b(X_i) \) refers to the characteristic quantization function, \( C \) represents the normalized constant, \( k(\cdot) \) is the kernel function and \( u \) refers to the feature index (if the feature point belongs to the \( u \)-th feature index interval, then \( \delta = 1 \); otherwise, \( \delta = 0 \)).

C. FITNESS FUNCTION

The fitness function value \( \text{fitness}(X_j) \) of image region \( j \) in the target tracking optimization problem in this study is defined as the similarity function value between image block
\( X_i \) and real target region \( X_r \) (the optimal solution found in the last frame). The Bhattacharyya function \( \rho(X_i) \) is used to determine the similarity between different image blocks [32]. The fitness function can be expressed as follows:

\[
\begin{align*}
\rho(X_i) &= \rho(p(X_i), p(X_r)) = \frac{1}{N} \sum_{i=1}^{N} p_i(X_i) p_i(X_r) \\
\text{fitness}(X_i) &= \sqrt{1 - \rho(X_i)}
\end{align*}
\]

where \( p_i(X_j) \) and \( p_i(X_r) \) are the eigenfunction values of the \( i \)-th dimension of the two samples \( X_j \) and \( X_r \), respectively.

**D. SCALE ADAPTIVE ADJUSTMENT METHOD OF TRACKING FRAME**

The scale \( \lambda \) of the tracking frame of the traditional trackers is fixed in the whole tracking process and therefore cannot easily adapt to the change of the target scale. It is also simple to mix too many invalid features or lose some effective features, which affects the accuracy and efficiency of the algorithm. Therefore, we propose a tracking frame scale adaptive adjustment model, which is expressed as follows:

\[
\begin{align*}
\lambda_{x,t} &= \lambda_{x,t-1} \cdot (0.75 \cdot \lambda_{x,t-1} + 0.25 \cdot \lambda_{y,t-1}) \\
\lambda_{y,t} &= \lambda_{y,t-1} \cdot (0.75 \cdot \lambda_{y,t-1} + 0.25 \cdot \lambda_{y,t-1}) \\
d_t &= \frac{1}{M} \sum_{i=1}^{M} \sqrt{(x_{i,t} - x_{t-1})^2 + (y_{i,t} - y_{t-1})^2} \\
d_{t,t-1} &= \frac{1}{M} \sum_{i=1}^{M} \sqrt{(y_{i,t} - y_{t-1})^2}
\end{align*}
\]

where \( (x_{t,i}, y_{t,i}) \) represents the position of the target center at time \( t \) (determined by the last frame), \( (x_{t,i}, y_{t,i}) \) refers to the position of individual \( i \) at time \( t \) and \( M \) is the number of individuals whose fitness is larger than the threshold \( w_T \) (where \( w_T \) is set to 0.6 times the mean value of the individual fitness in this study).

**III. VISUAL TRACKING METHOD BASED ON IMPROVED FPA**

Compared with other classical swarm optimization algorithms, the biggest advantage of the newly developed FPA algorithm is that it has both excellent global exploration ability and local development ability, which is also the main reason why this paper proposes to introduce FPA algorithm into machine vision target tracking. This study introduces a position update equation of the FPA as the main optimization method of the target tracking process. In addition, considering that the traditional FPA still faces problems such as a high probability of falling into local extrema, a slow convergence efficiency at the later stages, and a high risk of algorithm premature convergence. Therefore, we propose an improved FPA algorithm (GTFPA) based on the GSA and mutation mechanism via a trigonometric function.

**A. STANDARD FPA**

Flower pollination in nature is an amazing evolutionary process. Nearly 90% of the cross-pollination of flowering plants is carried out through long-distance pollination by pollinators such as bees, butterflies and birds, and their behavior follows the Levy distribution. The remaining 10% of self-pollination does not require pollinators and generally spreads through wind media to achieve short distance pollination. Yang [33] proposed the FPA inspired by flower pollination behavior. In this algorithm, global and local searches simulate the two processes of pollination, respectively, to find the optimal solution, which has the advantages of strong global and local search ability. The standard FPA can be divided into the following steps:

1) Initialization of the control parameters, including sample size \( N \), maximum number of iterations \( T \) and transformation probability \( p \) of the global and local searches.

2) Initialization of the sample set, randomly generation of the initial solution \( x_1, x_2, \cdots, x_n \) and calculation of the corresponding fitness value.

3) Determination of the optimal solution \( g_{best_0} \) and its fitness value \( f(g_{best_0}) \) from the current sample set.

4) Generation of a new sample set, a local or global search according to the conversion probability, and updating of the formula as follows:

\[
x_i^{t+1} = \begin{cases} 
x_i^t + \gamma (g_{best} - x_i^t), \text{rand} > p \\
x_i^t + \varepsilon (x_j^t - x_k^t), \text{rand} \leq p
\end{cases}
\]

where \( x_i^t \) is the pollen of the \( t \)-th generation, \( x_j^t \) and \( x_k^t \) represent pollen \( j \) and \( k \), respectively, randomly selected from different flowers of the same plant during the local search, which can enhance the diversity of the population. And \( p \) is the transformation probability of the global and local searches, \( \varepsilon \in U[0,1] \), \( \gamma \) represents the step size adjustment factor.
the search process and parameter $L$ represents pollination intensity, which follows the Levy distribution and its expression is as follows [34]:

$$L(\lambda) = \frac{\lambda \Gamma(\lambda) \sin(\pi \lambda / 2)}{\pi} \frac{1}{s^{1+\lambda}} \quad (s \geq s_0 > 0)$$

$$s = \frac{\mu}{|v|^{1/\lambda}} \quad (\mu \sim N(0, \sigma^2), \nu \sim N(0, 1))$$

$$\sigma^2 = \left\{ \begin{array}{ll}
\Gamma(1 + \lambda) & 
\sin(\lambda \cdot \pi \cdot 0.5) \\
\Gamma(1 + \lambda) / 2 & 
2^{(\lambda-1)/2}
\end{array} \right\}^{2^\lambda}$$

where $\Gamma(\lambda)$ represents the standard gamma function, and $\lambda$ takes the value 1.5 [34].

5) Calculation of the optimal solution and fitness value of the updated population.

6) Repetition of step 4) and 5) until the maximum number of iterations is reached.

B. GTFPA: AN IMPROVED FPA

This section focuses on search strategy optimization, population diversity improvement and parameter optimization to optimize the standard FPA.

1) IMPROVED GLOBAL SEARCH BASED ON GSA

The GSA was first proposed by Rashedi et al. [35]. Its main principle is as follows. The process of searching for optimization imitates the universal gravitation phenomenon in nature by endowing high-quality solutions with more mass and gravity, and guiding the sample set to converge to high-quality solutions. Different from the ant colony algorithm and other swarm intelligence algorithms, the GSA realizes the sharing of optimization information between different sample individuals through the interaction of universal gravitation in the process of searching for the optimal solution, and can perceive the optimization situation independently of external environmental factors.

The variables describing individual attributes include position, inertial mass, active gravitational mass and passive gravitational mass. The position is the solution of the optimization problem, and the three variables related to quality are determined by the fitness function. In the iterative process of the algorithm, individual evolution can be guided by adjusting the mass size of individual samples, and finally the sample set can converge under the influence of heavier individuals to find the individual with the largest inertial mass, i.e., the optimal solution of the optimization problem.

The GSA randomly generates the initial position and speed of the individual at the beginning of the iteration. Assuming that the sample set contains $N$ individuals moving at a certain speed in the $D$-dimensional search space, the position of the $i$-th individual can be expressed as follows:

$$X_i = (x_i^1, x_i^2, \cdots, x_i^k, \cdots, x_i^D), \quad i = 1, 2, \cdots, n \quad (9)$$

where $x_i^k$ represents the position of individual $i$ on the $k$-th dimension.

According to the law of universal gravitation, the interaction force between individuals $i$ and individual $j$ in the $k$-dimensional space at time $t$ is defined as:

$$F^k_{ij} = G(t) \frac{M_{pi}(t) \times M_{pj}(t)}{R_{ij}(t)^{\alpha}} (x_i^k(t) - x_j^k(t)) \quad (10)$$

where $M_{pi}(t)$ refers to the inertial mass acting on individual $i$; $M_{pj}(t)$ is the inertial mass of the individual $j$, $\varepsilon$ is an infinitesimal constant and $G(t)$ is the gravitational coefficient at time $t$, and its magnitude is inversely related to the number of iterations, which can balance the global and local search ability of the algorithm. The expression of $G(t)$ is as follows:

$$G(t) = G_0 \times e^{-\alpha t} \quad (11)$$

where $T$ is the maximum number of iterations, $G_0$ and $\alpha$ are constants ( $G_0 = 100$ and $\alpha = 20$ according to Rashedi's simulation experiment) and $R_{ij}$ is the Euclidean distance between individuals $i$ and $j$, calculated as follows:

$$R_{ij}(t) = \|X_i(t) - X_j(t)\|_2 \quad (12)$$

The larger the individual's inertial mass $M_i(t)$ is, the greater its gravitational pull on other individuals, the more likely it is to move to the center of the sample set, and the closer its position is to the optimal solution. $M_i(t)$ is updated as follows:
where $\text{fitness}(t)$ refers to the fitness value of individual $i$ at time $t$ and while $\text{worst}(t)$ and $\text{best}(t)$ respectively represent the worst and best fitness values, respectively.

The gravitational attraction of individual $i$ in the $k$-th dimension is the sum of the gravitational forces of all other individuals:

$$ F_i^k(t) = \sum_{j \neq i}^{n} \text{rand}_j \text{fitness}_j^k(t) $$

where, $\text{rand}_j$ is a random number in $[0,1]$, $n_{\text{best}}$ is the number of individuals with high quality at time $t$. The acceleration of individual $i$ in the $k$-dimensional space at time $t$ is:

$$ a_i^k = \frac{F_i^k(t)}{M_i(t)} $$

In the process of iteration $t$, the updating formula of individual velocity and position is as follows:

$$ V_i^k(t+1) = \text{rand}_i \times V_i^k(t) + a_i^k (t) $$
$$ X_i^k(t+1) = X_i^k(t) + V_i^k(t+1) $$

where $\text{rand}_i$ is a random number between $[0,1]$.

By embedding the GSA into the global search process of the FPA, the uneven random walk of the flower pollen sample set in Levy flight can be restrained by the dual constraints of Levy flight and inter-individual gravitation to guide the population to search for the optimal solution more efficiently. By combining the FPA global search formula and the GSA acceleration formula, it can be seen that in the improved FPA algorithm based on the GSA, the acceleration generated by the interaction force between flowers directly affects the size and direction of the iteration of flower position. In the GSA-improved FPA, the position iteration formula of the flower pollination global search process is updated as follows:

$$ x_i^{t+1} = a_i^t + \eta \cdot (g_{\text{best}} - a_i^t) $$

2) IMPROVED LOCAL SEARCH OF MUTATION OPERATION BASED ON TRIGONOMETRIC FUNCTION

Since the FPA algorithm mainly focuses on the local search in the late iteration, and the similarity of pollens increases, which leads to the loss of diversity of pollen population, the algorithm is prone to premature convergence and then falls into local optima [36-37]. In order to improve the population diversity in the late iteration of the algorithm, a stochastic perturbation factor should be added to the standard local search formula for flower pollination. Meanwhile, in order to avoid random disturbance affecting convergence efficiency too randomly, this study proposes an improved local search method for flower pollination based on variation operation performed by a trigonometric function, as shown in the following formula:

$$ x_i^{k+1} = x_i^k + f(\beta) \times |x_j^k - x_i^k|(k, j \neq i) $$
$$ f(\beta) = \begin{cases} \eta \sin(\beta), & \text{rand} < 0.5 \\ \eta \cos(\beta), & \text{rand} \geq 0.5 \end{cases} \text{rand} \in U(0,1) $$
$$ \eta = w \cdot \left(1 - \frac{t}{T}\right)^2 $$

where $\beta \in U[0,2\pi]$, $T$ is the maximum number of iterations and $w$ is a constant. When $w$ is set as a constant within the value range of $[0,1]$, the value range of the trigonometric function $f(\beta)$ is $[-1,1]$, which is in line with the local optimization characteristics of the sines and cosine functions [38]. In this study, $w$ is set as 1. In the local search formula of the original FPA algorithm, $x_i^j$ and $x_i^k$ are pollens of different flowers of the same plant. These two values are randomly selected from the current population, which is blind and not conducive to improving the convergence efficiency. In the above formula, the value range of trigonometric function $f(\beta)$ is $[0,1]$. In addition, the coefficient $\eta$ decreases with the number of iterations, so that this trigonometric function can effectively guide flower pollination to strengthen local search ability in the later iteration of the algorithm.

3) DYNAMIC CONVERSION PROBABILITY

The FPA randomly selects the global search or local search according to the conversion probability $p$, whose value will affect the evolution direction and optimization performance of the algorithm [39]. If $p$ is too small, the algorithm is difficult to converge due to the large number of global search operations. If the value of $p$ is too large, the algorithm can easily fall into local optima because it performs more local
searches [40-41]. In conclusion, in the standard FPA, the conversion probability $p$ is fixed. However, in the actual optimization process, $p$ plays a key role in adjusting the local search and global searches, which affects the balance of global or local search weight. In order to make the initial iteration more inclined to the global search, the value of $p$ should be slightly larger at the beginning. On the contrary, local searches should be more prevalent at the end of the iteration, so $p$ should take a smaller value at the end of the iteration. Therefore, the fixed conversion probability of standard FPA algorithm needs to be reformed.

Considering the nonlinear characteristics of target tracking problem and the optimization process should meet the requirements of full exploration in the early stage and accelerated convergence in the later stage. In this study, exponential function is used to adjust the conversion probability of dynamic transformation in real time with the number of iterations in the optimization process, and the expression is as follows:

$$p = \min p + (\max p - \min p) \cdot e^{t/T-1}$$

(19)

where $\min p$ and $\max p$ are respectively the upper limits and lower limit of conversion probability. In this study, the values are 0.9 and 0.2, respectively.

The balance between global search and local searches is realized by dynamically adjusting $p$, which makes the global search ability enhanced in the early iteration and the local search ability strengthened in the late iteration. The new conversion probability formula can not only make the algorithm fully explore the search space in the early stage, increase the accuracy of the global optimal value, but also ensure the speed of convergence in the late iteration.

Through the relevant work in Section 3.2, this study establishes an improved FPA, GTFPA, in terms of search strategy optimization, population diversity improvement, and parameter optimization.

C. TARGET TRACKING FLOW BASED ON GTFPA

The target tracking process based on GTFPA is expanded as follows:

1) Parameter initialization: set sample number $S$, maximum iteration number $T$, conversion probability $p$, and initial universal gravitation parameter $G_0$.

2) Randomly initialize the position of the population, calculate the fitness value of each solution, and solve the optimal value and the worst value of the current two-system load deviation.

3) Calculate the individual gravitation coefficient $G_i$ according to Equation (11).

4) Calculate the inertial mass $M_i(t)$ according to Equation (13).

5) Calculate the sum $F_i^k(t)$ of the gravitation force of individual $i$ according to Equation (14).

6) Obtain the acceleration $a_i^k$ of individual $i$ according to Equation (15).

7) Calculate the transformation probability $p$ according to Equation (19) and judge whether to carry out the global or local search, which are executed according to Formula (17) or Formula (18) respectively, according to $p$.

8) Calculate the fitness value, update the global optimal solution, and update the optimal target location; judge whether the end condition of the algorithm is met. If so, exit and output the optimal solution; otherwise, repeat steps 3) to 9).

The flow chart of the target tracking algorithm based on the GTFPA algorithm is shown in Figure 1.
IV. EXPERIMENTAL ANALYSIS

We used MATLAB to implement the proposed tracker on a machine equipped with an Intel Core i-7-4790 CPU @ 3.60GHz with 32 GB RAM. Set the maximum iteration number T as 500, the sample number S as 70, initial conversion probability $p$ as 0.642 and initial universal gravitation parameter $G_0$ as 100. The proposed GTFPA tracking method achieves an average tracking speed of 27 frames per second (FPS). For experimental verification, we employ OTB2015 [42] and VOT2018 [43], which contain hundreds of video sequences and more than ten tracking scenes and can effectively test the success rate, accuracy and stability of the trackers. We evaluate the tracking accuracy, efficiency, and adaptability of the tracker in different tracking scenarios by carrying out qualitative and quantitative comparison between our tracker with nine classical generative trackers in OTB2015 including the ECO [7], C-COT [8], MUSTer [9], SRDCFdecon [10], BACF [11], LMCF [12], SAMF [13], DSST [14] and MSPF [15]. We evaluate the robustness and stability of these trackers by carrying out statistical comparison between our tracker with eight state-of-the-art tracking methods in VOT2018 including DeepSTRCF [16], SiamVGG [17], ECO, GTFPA, MCCT [18], C-COT, Staple, SRDCF [44] and DSST.

A. QUALITATIVE COMPARISONS

In this section, we evaluated the tracking performance of GTFPA in three aspects: precision, efficiency and adaptability to different tracking scenarios. We selected eight challenging tracking scenes including illumination variation, motion blur, deformation, complex background, occlusion, rotation, scale variation and low resolution. As illustrated in Fig.4, the qualitative comparison results prove that GTFPA, ECO and C-COT can effectively capture the target in all tracking scenarios. Their tracking frame can always fit the target and adapt well to the change of target scale. The tracking frame of other algorithms deviates from the target obviously or loses the target in different degrees in multiple tracking scenes.
FIGURE 2. Comparison of ten different trackers on eight challenging sequences (from top to bottom: Car2, BlurCar4, Dancer2, MountainBike, Skiing, Singer2, Gym and Skating2, which contain illumination change, motion blur, deformation, complex background, low resolution, size change, rotation and occlusion).

| Attribute | IV | SV | OCC | DEF | MB | FM | IPR | OPR | OV | BC | LR | Overall |
|-----------|----|----|-----|-----|----|----|-----|-----|----|----|----|---------|
| ECO       | 0.914 | 0.881 | 0.908 | 0.858 | 0.910 | 0.866 | 0.901 | 0.903 | 0.909 | 0.936 | 0.895 | 0.912 |
| C-COT     | 0.884 | 0.882 | 0.904 | 0.856 | 0.906 | 0.870 | 0.877 | 0.898 | 0.895 | 0.882 | 0.885 | 0.899 |
| GTFPA     | 0.876 | 0.871 | 0.889 | 0.854 | 0.891 | 0.863 | 0.883 | 0.879 | 0.868 | 0.895 | 0.859 | 0.875 |
| MUSTer    | 0.836 | 0.887 | 0.833 | 0.849 | 0.846 | 0.847 | 0.864 | 0.858 | 0.801 | 0.879 | 0.796 | 0.861 |
| SRDCFdecon | 0.87 | 0.862 | 0.842 | 0.838 | 0.872 | 0.852 | 0.825 | 0.822 | 0.796 | 0.883 | 0.823 | 0.870 |
| BACF      | 0.823 | 0.875 | 0.866 | 0.837 | 0.846 | 0.847 | 0.849 | 0.865 | 0.851 | 0.862 | 0.856 | 0.882 |
| LMCF      | 0.812 | 0.807 | 0.799 | 0.864 | 0.774 | 0.788 | 0.783 | 0.816 | 0.764 | 0.776 | 0.653 | 0.782 |
| SAMF      | 0.753 | 0.774 | 0.708 | 0.762 | 0.703 | 0.776 | 0.797 | 0.772 | 0.739 | 0.758 | 0.739 | 0.739 |
| DSST      | 0.623 | 0.621 | 0.589 | 0.595 | 0.628 | 0.611 | 0.585 | 0.599 | 0.575 | 0.628 | 0.589 | 0.620 |

TABLE 2

| Attribute | IV | SV | OCC | DEF | MB | FM | IPR | OPR | OV | BC | LR | Overall |
|-----------|----|----|-----|-----|----|----|-----|-----|----|----|----|---------|
| ECO       | 0.713 | 0.669 | 0.680 | 0.633 | 0.683 | 0.678 | 0.655 | 0.673 | 0.660 | 0.700 | 0.617 | 0.691 |
| C-COT     | 0.682 | 0.658 | 0.674 | 0.614 | 0.679 | 0.673 | 0.627 | 0.652 | 0.648 | 0.652 | 0.619 | 0.673 |
| GTFPA     | 0.691 | 0.647 | 0.677 | 0.621 | 0.663 | 0.659 | 0.633 | 0.641 | 0.632 | 0.628 | 0.597 | 0.667 |
| MUSTer    | 0.652 | 0.607 | 0.611 | 0.568 | 0.612 | 0.644 | 0.591 | 0.602 | 0.577 | 0.595 | 0.561 | 0.642 |
| SRDCFdecon | 0.651 | 0.608 | 0.603 | 0.589 | 0.623 | 0.636 | 0.586 | 0.606 | 0.540 | 0.631 | 0.546 | 0.634 |
| BACF      | 0.641 | 0.589 | 0.596 | 0.544 | 0.597 | 0.627 | 0.562 | 0.617 | 0.564 | 0.647 | 0.553 | 0.632 |
| LMCF      | 0.628 | 0.575 | 0.617 | 0.571 | 0.579 | 0.607 | 0.587 | 0.611 | 0.598 | 0.638 | 0.544 | 0.624 |
| SAMF      | 0.605 | 0.556 | 0.556 | 0.524 | 0.541 | 0.578 | 0.573 | 0.590 | 0.601 | 0.640 | 0.531 | 0.577 |
| DSST      | 0.597 | 0.537 | 0.594 | 0.513 | 0.524 | 0.532 | 0.533 | 0.593 | 0.545 | 0.583 | 0.483 | 0.554 |
| MSPF      | 0.475 | 0.441 | 0.440 | 0.411 | 0.447 | 0.455 | 0.411 | 0.438 | 0.373 | 0.463 | 0.384 | 0.452 |

B. QUANTITATIVE COMPARISONS

To further evaluate the tracking performance of GTFPA comprehensively, we quantitatively compare our tracker with
the classical trackers in OTB-2015 via success rate (the percentage of successful frames) and precision rate (the ratio of tracking frames whose center position error is smaller than a given threshold). As illustrated in Tables 1 and 2, the GTFPA performed well in all 11 tracking scenarios of OTB2015: In terms of success and precision, it basically ranked top 4, and ranked top 3 in at least nine scenes. Its tracking accuracy and success rate had no obvious disadvantage compared with other advanced trackers.

C. STATISTICAL COMPARISON

To evaluate the robustness and stability of the GTFPA, we carry out a statistical comparison with the VOT2018 database.

This section introduces some new tracking methods that perform very well in VOT2018, including DeepSTRCF [16], SiamVGG [17] and MCCT [18] for better evaluation of the GTFPA. In statistical comparison, we compare the GTFPA with these classical generative trackers in three aspects: average overlap (EAO), accuracy (Acc.) and robustness (R. for short, measured by failure rate). As illustrated in Table 3, GTFPA ranked second in EAO, fourth in ACC, and third in R. It turns out that GTFPA is more competitive in robustness and stability than other classical generative trackers. As shown in Table 4, the tracking speed of the GTFPA is 27 frames per second, ranking in the third place. The tracking efficiency of the GTFPA is not obviously inferior to other classical generative trackers.

V. CONCLUSION

This study proposed a robust visual tracking algorithm based on the FPA. Specifically, in this study, a tracking frame adaptive adjustment model was proposed, which brings a new method to effectively reduce the invalid background features of tracking frame and improve the proportion of effective features. Meanwhile, we improved the global optimization of the traditional FPA by the GSA. We also improved the local optimization process of the FPA by a mutation mechanism based on a trigonometric function. Moreover, we presented the dynamic adjustment mechanism of the FPA algorithm transformation probability, which balances the global and local optimization process and improves its searching efficiency. To verify the tracking performance, OTB2015 and VOT2018 datasets were used to carry out qualitative, quantitative and statistical comparison with other classical generative tracking methods. The tracking results in a variety of complex tracking scenarios show that the proposed GTFPA tracking algorithm performs well in efficiency, accuracy and robustness.

In future work, more robust features could be employed. Issues related to automatic detection and target behavior analysis are also of concern.

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