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# Visual Tracking with Breeding Fireflies using Brightness from Background-Foreground Information

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***Abstract*—Visual target tracking involves object localization in image sequences. This is achieved by optimizing image feature similarity based objective functions in object state space. Meta-heuristic algorithms have shown promising results in solving hard optimization problems where gradients are not available. This motivated us to use Firefly algorithms in visual object tracking. The object state is represented by its bounding box parameters and the target is modeled by its color distribution. This work has two significant contributions. First, we propose a hybrid firefly algorithm where genetic operations are performed using Real-coded Genetic Algorithm(RGA). Here, the crossover operation is modified by incorporating parent velocity information. Second, the firefly brightness is computed from both foreground and background information (as opposed to only foreground). This helps in handling scale implosion and explosion problems. The proposed approach is benchmarked on challenging sequences from VOT2014 dataset and is compared against other baseline trackers and metaheuristic algorithms.**

## I. Introduction

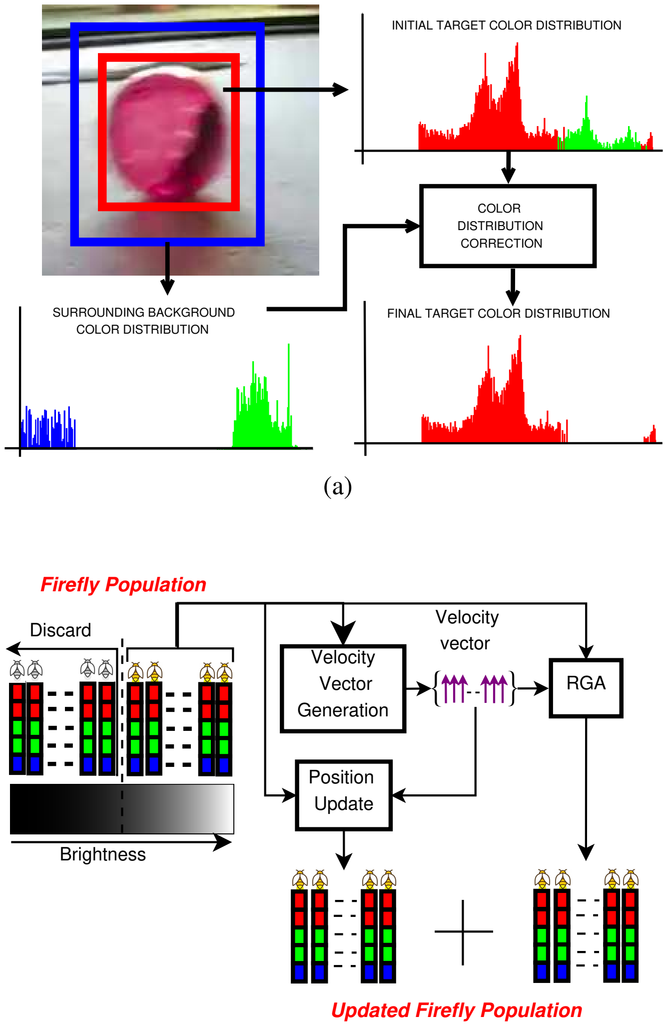
Visual object tracking remains a challenging research area in computer vision on account of the problems arising from occlusions, background clutter, object deformations, illumination changes, scaling and rotations. Researchers have traditionally contributed to two components of tracking. First, object modeling through feature proposals [1]–[5] and statistical models in generative, discriminative and hybrid frameworks. Second set of contributions are made in localization algorithms. This work focuses on object localization algorithms.

Object localization poses tracking as an optimization problem. Here, the objective of localizing the object through feature similarity or classifier score is maximized using a search in object state space. Such a search can be executed using gradient based methods (mean-shift tracking [6]), stochastic approaches (Particle Filter [2]) or brute force techniques [7].

Localization algorithms in tracking include mean-shift [6], Kalman filter [1], particle filter [8] etc. Particle filter based approach has dominated tracking due to its simplicity and the ability to provide localization in spaces (scale, orientation etc.) where gradients are not available. Localization involves search in object state space and convergence depends on the dimension of object state vector. Metaheuristic algorithms were found to provide better convergence in such cases. These algorithms generate solutions by following a set of rules in a random yet directed manner. This directed approach leads to better convergence and the randomness helps in search space exploration (or exploitation). Some of these approaches include Genetic Algorithm (GA) [9], Particle Swarm Optimization (PSO) [10] , Firefly Algorithm (FA) [11] etc. Firefly Algorithm was found to be better among these approaches as given in [11]. This motivated us to propose modifications on the basic firefly algorithm.

Particle Swarm Optimization (PSO) algorithm maintains a set of particles (by forming a swarm) where each particle represents a candidate solution. The position and velocity of each particle are updated in every iteration. This update is performed using the best position of a particle from past iterations and the global best position among all particles. The particles travel towards the (supposedly) global optima using velocity and position update rules. In PSO, new particles are not bred and that reduces diversity in solutions. This often lead to local convergence. Breeding swarm strategies [12], [13] were proposed to overcome such problems by combining PSO with Real-coded Genetic Algorithm (RGA) [14]. Here, a part of the population is generated using PSO algorithm and the remaining particles are generated using a novel velocity propelled average crossover (VPAC) operator.

We have formulated the localization problem of visual object tracking as an optimization problem. We propose to solve this optimization problem using an enhanced version of firefly algorithm. The object bounding box parameters (centroid, scale and orientation) form the solution vector in search space. The fireflies are associated with these solution vectors. The firefly brightness is derived from target and candidate model similarity that uses both foreground and background information. This proposal is found to handle scale implosion and explosion problems leading to better object localization. The firefly algorithms are generally enhanced with genetic algorithm by using differential evolution strategies. However, Settles et.al. [12] established the superiority of his VPAC operator over differential evolution schemes. This motivated us to introduce crossover operation with parent velocity information in breeding fireflies. This approach is benchmarked




(b)

Fig. 1. **(a)** Color distribution of foreground (red) and background (blue). Common features, highlighted in green are removed from initial target color distribution to obtain final target model (color distribution). **(b)** Proposed hybrid firefly algorithm for tracking. Object bounding box parameters are combined in solution vector containing centroid (red), scaling in width and height (green) and orientation (blue). A part of population is updated following basic firefly algorithm. The remaining population is bred using velocity propelled crossover operator.

on challenging sequences from VOT2014 [15] dataset. To summarize, our proposal has the following contributions

1) Combination of Firefly and RGA with velocity information incorporated in crossover operation.
2) Firefly brightness computed from both foreground and background for better object localization.

The rest of the paper is organized as follows. Our proposal of target and candidate model representation, hybrid firefly algorithm and firefly brightness measure are explained in Section II. Our experiments with the proposed tracker is presented in Section III. Section IV concludes this work and discusses the possible future extensions.

## II. Proposed Work

This work proposes a tracker in a generative framework that uses feature distribution for modeling target (initial frame) and candidates (later frames for localization). Object tracking is formulated as an optimization problem with an objective of maximizing similarity between target and candidate feature distributions. In this context, the generic framework and our special cases of (color) feature distribution based target and candidate model construction are explained in Sub-section II-A. This optimization problem is solved by using our proposed hybrid firefly algorithm. The basic algorithm and its proposed extension to breeding fireflies by introduction of RGA (genetic operation with velocity information) is discussed in Sub-section II-B. Object state vectors or solutions are associated with fireflies. The firefly brightness function is derived from the similarity between target and candidate models. The proposed brightness measure uses both foreground and background information for better localization and is described in Sub-section II-C. The target and candidate models are described next.

### A. Target and Candidate Model

This work assumes the special case of tracking algorithms in generative framework that use both target and candidate models for object localization. In a general formulation, the target object is initially identified by its (minimum) bounding polygon $\mathbf{B}_T(0)$ in first frame $\mathbf{I}_0$ of sequence. The tracking algorithm generally constructs an object model $\mathbf{M}_T = \mathbf{g}(\mathbf{B}_T(0), \mathbf{I}_0)$ using feature distributions computed from $\mathbf{B}_T(0)$. In $t^{th}$ frame $\mathbf{I}_t$, similar process is applied to construct candidate model $\mathbf{M}_C(t) = \mathbf{g}(\mathbf{B}_C(t), \mathbf{I}_t)$ from region proposal $\mathbf{B}_C(t)$. The function $\mathbf{g}(\mathbf{B}, \mathbf{I})$ is specific to a tracking algorithm that computes a certain model from a region proposal $\mathbf{B}$ in frame $\mathbf{I}$. The candidate region proposal is generally represented by geometrical properties of the polygon $\mathbf{B}_C(t)$. Most tracking algorithms define a (dis)similarity measure $\mu(\mathbf{M}_T, \mathbf{M}_C(t)) \in [0,1]$ between the target and candidate model. This measure is used to test validity of region proposals thereby leading to object localization.

In this work, the target object is initially identified with its minimum bounding rectangle $\mathbf{B}_T^+(0)$ as shown in figure 1(a). A concentric and scaled up rectangle $\mathbf{B}_T^\pm(0)$ is around $\mathbf{B}_T^+(0)$ contains both target and scene background. We consider the region $\mathbf{B}_T^-(0) = \mathbf{B}_T^\pm(0) - \mathbf{B}_T^+(0)$ that contains only background information. Our proposal constructs target $(\mathbf{M}_T^+(0))$ and surrounding background models $(\mathbf{M}_T^-(0))$ as $m$-bin color distributions learned from $\mathbf{B}_T^+(0)$ and $\mathbf{B}_T^-(0)$ respectively. These models are as

$$\mathbf{M}_T^+[u] \quad = \quad L^+ \sum_{i=1}^{n^+} k(\|\mathbf{x}_i^\star\|^2)\delta[b(\mathbf{x}_i^\star) - u] \qquad (1)$$

$$\mathbf{M}_T^-[u] \quad = \quad L^- \sum_{i=1}^{n^-} \delta[b(\mathbf{x}_i^\star) - u] \qquad (2)$$

where, $b(\mathbf{x})$ computes the color bin of the pixel position $\mathbf{x}$, $\delta[\cdot]$ is the Kronecker delta function and $L^+$, $L^-$ are normalization constants, $n^+$, $n^-$ are the respective number of pixels in $\mathbf{B}_T^+(0)$, $\mathbf{B}_T^-(0)$. A modifier target model $\mathbf{M}_T^{m+}(0)$ is created from $\mathbf{M}_T^+(0)$ using the background information in $\mathbf{M}_T^-(0)$. A shared color bin $l$ is suppressed if $\mathbf{M}_T^-(0)[l]$ exceeds $\mathbf{M}_T^+(0)[l]$ (Equation 4).

$$\mathbf{M}_T^{m+}(0)[l] = \mathbf{M}_T^+(0)[l]\mathcal{I}_A(l) \quad (3)$$

$$\mathbf{A} = \{l : \mathbf{M}_T^+(0)[l] > \mathbf{M}_T^-(0)[l]\} \quad (4)$$

where $\mathcal{I}_A(l)$ is the indicator function such that $\mathcal{I}_A(l) = 1$ if $l \in A$ and 0, otherwise. The modified target model $\mathbf{M}_T^{m+}(0)$ is used for object localization.

For localizing object in current frame $\mathbf{I}_t$, region proposals $\mathbf{B}_C^{\pm}$ are generated as solutions in hybrid firefly algorithm. Subscript $t$ is dropped for notational convenience in following discussions. It has two concentric regions $\mathbf{B}_C^+$ representing the foreground (probably containing target) and surrounding background represented as $\mathbf{B}_C^-$. Our proposal represents the foreground ($\mathbf{M}_C^+$) and background ($\mathbf{M}_C^-$) candidate models as

$$\mathbf{M}_C^+[u](y) = L_C^+ \sum_{i=1}^{nc^+} k\left(\left\|\frac{\mathbf{y}-\mathbf{x}_i}{h}\right\|^2\right)\delta[b(\mathbf{x}_i)-u] \quad (5)$$

$$\mathbf{M}_C^-[u](y) = L_C^- \sum_{i=1}^{nc^-} \delta[b(\mathbf{x}_i)-u] \quad (6)$$

where, $\mathbf{y}$ is the centroid of $\mathbf{B}_C^+$ as well as $\mathbf{B}_C^-$, $h$ is the bandwidth of the kernel, $L_C^+, L_C^-$ are normalization constants, $nc^+$, $nc^-$ are the respective number of pixels in $\mathbf{B}_C^+$, $\mathbf{B}_C^-$.

The goal of tracking is to search for optimal candidate bounding box parameters for better object localization. We perform this by using our proposed extension of firefly algorithm. This hybrid firefly algorithm is described next.

### *B. Hybrid Firefly Algorithm*

The Firefly algorithm (FA) is a biologically inspired evolutionary technique derived from flashing pattern of tropical fireflies [16], [17]. This algorithm treats each solution in search space as a firefly. These fireflies move in search space based on attraction towards brighter fireflies. Brightness of a firefly is defined as a function of the solution or the objective function itself. Each firefly gets attracted to other brighter fireflies. This attraction is directly proportional to brightness and falls exponentially with distance. These attractions induce motion on fireflies in the search space. New positions of the moving fireflies lead to new (and possibly improved) solutions. Each iteration of this algorithm involves incremental movement of fireflies (solutions) in a population.

The firefly population $\mathbf{Z}_0 = \{\mathbf{z}_i(0), i = 1, \ldots nz\}$ is randomly initialized in search space with a population size $nz$. We also compute the brightness (objective function) values of fireflies as $\mathbf{BZ}_0 = \{bz_i(0), i = 1, \ldots nz\}$. Consider the population $\mathbf{Z}_{\tau-1}$ in the $(\tau-1)^{th}$ iteration with brightness

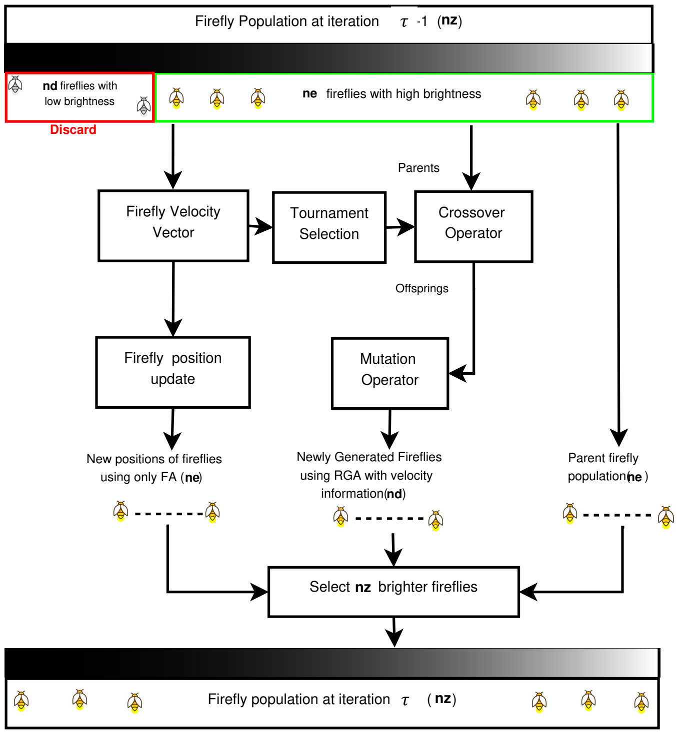



Fig. 2. Illustrating the proposed approach of breeding fireflies.

values $\mathbf{BZ}_{\tau-1} = \{bz_i(\tau-1), i = 1, \ldots nz\}$. The attraction $\beta_{ij}(\tau-1)$ between fireflies $\mathbf{z}_i(\tau-1)$ and $\mathbf{z}_j(\tau-1)$ is defined as

$$\beta_{ij}(\tau-1) = \frac{\beta_0}{1+\gamma r_{ij}^2(\tau-1)} \quad (7)$$

where, $\beta_0$ is the attraction at $r = 0$, $\gamma$ is the light absorption coefficient and $r_{ij}(\tau-1) = \|\mathbf{z}_i(\tau-1) - \mathbf{z}_j(\tau-1)\|_2$.

If $bz_j(\tau-1) > bz_i(\tau-1)$, then the velocity $\mathbf{vz}_{ij}(\tau-1)$ of $\mathbf{z}_i(\tau-1)$ induced by $\mathbf{z}_j(\tau-1)$ is given by

$$\mathbf{vz}_{ij}(\tau-1) = \beta_{ij}(\tau-1)(\mathbf{z}_j(\tau-1)-\mathbf{z}_i(\tau-1))+\alpha(a-0.5) \quad (8)$$

where, $\alpha$ is a randomization parameter and $a \in [0, 1]$. The first term in equation 8 induces motion towards the brighter firefly by scaling it with attraction. The second term introduces a random but small distraction from this direction of motion. Let, $\mathbf{J}(\tau-1)$ be the set of all firefly indices such that $bz_j(\tau-1) > bz_i(\tau-1) \forall j \in \mathbf{J}(\tau-1)$. The next position $\mathbf{z}_i(\tau)$ of the $i^{th}$ firefly is derived from the net motion $\mathbf{vz}_i(\tau-1)$ induced on it and is given as

$$\mathbf{vz}_i(\tau-1) = \sum_{j \in \mathbf{J}(\tau-1)} \mathbf{vz}_{ij}(\tau-1) \quad (9)$$

$$\mathbf{z}_i^{new}(\tau-1) = \mathbf{z}_i(\tau-1) + \mathbf{vz}_i(\tau-1) \quad (10)$$

The brightness values at new positions $(\mathbf{z}_i^{new}(\tau-1); i = 1, \ldots nz)$ are evaluated. The best $nz$ from these (new positions) and $\mathbf{Z}_{\tau-1}$ are selected to form the next generation of fireflies $\mathbf{Z}_\tau$ with corresponding brightness values in $\mathbf{BZ}_\tau$.

The firefly algorithm (FA) searches for optimal solutions in a population based approach. Researchers have proposed hybrid firefly algorithms by introducing genetic operators in creating new fireflies [11]. These works have mostly used differential evolution [18] where one part of the population changes position using evolutionary techniques (GA or RGA [14]) and the other updates positions using the basic FA. However, these methods do not consider the velocity vectors in breeding fireflies and genetic operations are performed directly on the solution vectors. Settles et. al. [12] have introduced the contribution of velocities in crossover operation in context of hybrid PSO. Introduction of particle velocities in crossover has shown improvements over differential evolution schemes [18]. This motivated us to propose a hybrid firefly algorithm that breeds fireflies with parent velocity information. The proposed approach is described as follows.

As illustrated in figure 2, the fireflies in the population $\mathbf{Z}_{\tau-1}$ are first sorted in ascending order of brightness values. The first $nd = \lfloor br \times nz \rfloor$ ($br \in (0,1)$ is the breeding ratio) fireflies are discarded to form the elite population $\mathbf{Z}^{e}_{\tau-1} = \{\mathbf{z}^{e}_{i}(\tau-1); i = \dots ne\}$ ($ne = nz - nd$). The net motion vectors $\mathbf{vz}^{e}_{i}(\tau-1)$ ($i = 1, \dots ne$) of the elite fireflies (in $\mathbf{Z}^{e}_{\tau-1}$) are estimated using equation 9. New positions of elite fireflies are updated using their motion vectors (equation 10) to form the population $\mathbf{Z}^{e}_{fa}(\tau-1) = \{\mathbf{z}^{efa}_{i}(\tau-1); i = 1, \dots ne\}$.

The population gap generated by discarding $nd$ fireflies in $\tau^{th}$ iteration is filled up by breeding fireflies in $\tau^{th}$ iteration. Parent fireflies are repeatedly generated for offspring generation. Let, $\mathbf{z}^{e}_{k}(\tau-1), \mathbf{z}^{e}_{l}(\tau-1) \in \mathbf{Z}^{e}(\tau-1)$ be two parents chosen by the process of tournament selection. The offsprings $\mathbf{z}^{ebr}_{k}(\tau-1)$ and $\mathbf{z}^{ebr}_{l}(\tau-1)$ are generated through crossover operation combined with corresponding parent velocity information. This is performed using the following equations.

$$\mathbf{z}^{ebr}_{k}(\tau-1) = \frac{1}{2}(\mathbf{z}^{e}_{k}(\tau-1) + \mathbf{z}^{e}_{l}(\tau-1)) - \phi_k \mathbf{vz}^{e}_{k}(\tau-1) \quad (11)$$

$$\mathbf{z}^{ebr}_{l}(\tau-1) = \frac{1}{2}(\mathbf{z}^{e}_{l}(\tau-1) + \mathbf{z}^{e}_{k}(\tau-1)) - \phi_l \mathbf{vz}^{e}_{l}(\tau-1) \quad (12)$$

where, $\phi_k$ and $\phi_l$ are uniform random variables drawn from $[0.0, 1.0]$. In case of mutation operator, Gaussian mutation is used with zero mean and diagonal covariance matrix $\mathbf{\Sigma}$ to find new undiscovered positions which a firefly can reach. The parent fireflies are repeatedly sampled using tournament selection till $nd$ (or $nd+1$, if $nd$ is odd) firefly offsprings are generated. These offsprings form the population $\mathbf{Z}^{ebr}(\tau-1)$. The brightness values of $\mathbf{Z}^{e}_{fa}\tau-1$, $\mathbf{Z}^{ebr}(\tau-1)$ are computed and compared with that of $\mathbf{Z}_{\tau-1}$ to choose the brightest $nz$ fireflies. These fireflies (best solutions) form the population $\mathbf{Z}_{\tau}$ (with set of brightness values $\mathbf{BZ}_{\tau}$) for the next iteration.

The proposed hybrid firefly algorithm is applied to the problem of visual object tracking in dynamic scenes. The target object is modeled by its color distribution and is localized by its minimum bounding box. Bounding box parameters are stacked together to form solution vectors (fireflies) in the search space. The firefly brightness is defined using object localization confidence. The construction of solution vector and the proposed brightness measure are described next.

### C. Proposed Brightness Measure

Each firefly is represented by the state vector $\mathbf{z} = [c_x, c_y, s_x, s_y, \theta]$, ($\mathbf{z} \in \mathbf{R}^5$). The population is generated from region proposals obtained from current frame $\mathbf{I}_t$. The brightness of fireflies is derived from proposed target and candidate models. Two different formulations are used in this work. In the first approach, brightness $bz_i$ of $i^{th}$ firefly is derived from models $\mathbf{M}^{+}_{T}$ and $\mathbf{M}^{+}_{C}$ computed from the region proposals. This is defined as

$$bz^{f}_{i} = \rho(\mathbf{M}^{+}_{T}(0), \mathbf{M}^{+}_{C}) \quad (13)$$

where, $\rho(\cdot,\cdot)$ indicates the similarity measure computed as Bhattacharyya coefficient between two distributions. This brightness formulation is limited, as only foreground information is utilized. This measure can handle scale explosion (bounding box going larger). However, it fails in cases of scale implosion where the algorithm progressively selects smaller regions leading to an eventual collapse. To overcome this, one has to test for background information around the object. We propose a new formulation which not only maximizes the similarity between the target and candidate foreground but also minimizes the similarity between target foreground and candidate background. This is formulated as

$$bz^{fb}_{i} = \rho(\mathbf{M}^{+}_{T}, \mathbf{M}^{+}_{C}) \times (1 - \rho(\mathbf{M}^{+}_{T}, \mathbf{M}^{-}_{C})) \quad (14)$$

Here, the first term provides similarity with target model in object localization and stops scale explosion. The second term ensures the presence of maximal background in its immediate neighborhood thereby checking scale implosion.

## III. Experimental Results

The proposed localization algorithm using Firefly and RGA is used with two objective functions. First, the tracker FRGA-F that uses only foreground information in the objective function (Equation 13). Second, the tracker FRGA-FB using both foreground and background information (Equation 14). The performance of FRGA-F and proposed FRGA-FB are evaluated on challenging sequences from VOT-2014 dataset. The performance analysis is estimated using average overlap and failure rate. The overlap $\phi_t$ in a frame $\mathbf{I}_t$ is defined as

$$\phi_t = \frac{a\,(\mathbf{B}^{p}_{t} \cap \mathbf{B}^{g}_{t})}{a\,(\mathbf{B}^{p}_{t} \cup \mathbf{B}^{g}_{t})} \quad (15)$$

where, $\mathbf{B}^{p}_{t}$ is the tracker predicted bounding box, $\mathbf{B}^{g}_{t}$ is ground-truth bounding box and $a(\mathbf{B})$ signifies the area of a region $\mathbf{B}$ in an image $\mathbf{I}$. The average overlap measure is computed over an entire sequence. The tracker is reset when the overlap in a frame falls to zero. In such cases, the tracker is reinitialized after skipping 5 frames. Subsequent 10 frames are discarded from accuracy computation to reduce bias. The number of re-initializations over a sequence defines failure count (F). Our proposal involves stochastic search based algorithms. Thus, the experiments are repeated multiple times to obtain the performance statistics. The tracker performances obtained in different runs are averaged. These average values are reported as performance measures in Table I. These measures indicate the accuracy (A) and failure rate (FR) of each tracker. Higher accuracy indicates better overlap and lower failure rate signifies higher robustness. These measures are defined as

$$A = \frac{1}{N_{rep}} \sum_{r=1}^{N_{rep}} \phi_{avg}(r) \tag{16}$$

$$FR = \frac{1}{N_{rep}} \sum_{r=1}^{N_{rep}} F(r) \tag{17}$$

where, $N_{rep}$ indicates the number of repetitions of experiments on a sequence, $\phi_{avg} = \frac{1}{T_v} \sum_{t=1}^{T_v} \phi_t$ and $T_v$ is the valid number of frames used for accuracy computation. These performance measures are obtained using the VOT2014 toolkit [15].

The tracker is benchmarked on challenging sequences from VOT2014 dataset. These sequences are BALL, FERNANDO, GYMNASTICS, JOGGING, POLAR BEAR, SPHERE and SURFING. The performance of the proposed tracker is compared against the following baseline algorithmss – (a) FA using only foreground information and firefly algorithms for localization [19], (b) PF using only foreground information and particle filter (150 particles) for localization [8], (c) MatFlow [20], (d) LGTv1 [21], (e) IVT [22], (f) MIL [23], (g) PTp [24] and (h) BDF [20]. The performance analysis is presented in Table I.

We observe that the proposed tracker using foreground-background information and breeding firefly based localization provides good accuracy and lower failure rates. We believe that the discriminative nature of the objective function (Equation 14) led to this performance improvement which can be observed in terms of reduction in failure rate. The visual results of object tracking on some of these sequences are presented in figure 3. The trackers were evaluated using the VOT toolkit. This toolkit provides a platform for the comparison of different tracking algorithms.

Parameters chosen for implementation – Proposed FRGA was implemented with a population size of $N = 16$ for a maximum number of iterations $T_{max} = 7$. The search space for scaling parameter is set to $[s_x^{min}, s_x^{max}] = [0.7 \times w, 1.3 \times w]$, and $[s_y^{min}, s_y^{max}] = [0.7 \times h, 1.3 \times h]$; where $w$ and $h$ are the width and height of target object from previous frame $\mathbf{I}_t$ respectively. Search space for the orientation of the object is given as $[\theta_{min}, \theta_{max}] = [0, \pi]$. The Firefly algorithm parameters are set as $\beta_0 = 2$ and $\gamma = 0.01$. The randomization parameters are set to $\alpha = 1$ and $\lfloor N \times s \rfloor = 0.4$. Our work is concluded in next section along with discussion on possible future extensions of the work.

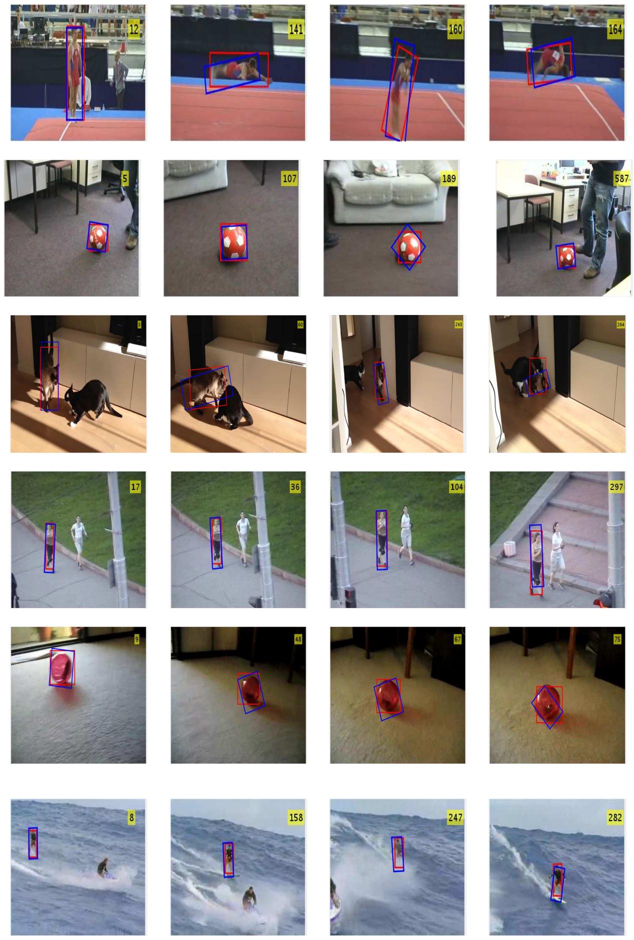


Fig. 3. Tracker output on sequences gymnastics,ball,fernando, jogging, sphere and surfing from VOT2014 dataset are given in first, second, third, fourth, fifth and sixth rows respectively. Tracker predicted bounding box is marked in blue and ground truth box is marked in red.

## IV. Conclusion

We introduced diversity in fireflies with Real-coded Genetic Algorithm. The modified formulation is used to provide localization in single object tracking. Object was modeled with its color distribution. New brightness function was defined by considering target candidate and its background also. It maximized the presence of object in foreground region and at the same time maximized the presence of background around it. This provided better discrimination against background. Proposed approach provided better localization and discrimination against background. Performance evaluation showed the effectiveness of the proposed tracker on challenging sequences from VOT2014 dataset.

The present work can be extended in the following directions. First, present work has only focused on object localization. Thus, color features were used for simplicity. Tracking algorithms in generative and discriminative frameworks have investigated other features like gradient distributions [2], local binary patterns [4], SIFT [5], sparse codes [3], classifier scores

TABLE I

ACCURACY(A) AND FAILURE RATE (FR) OF PROPOSED TRACKER (FRGA-FB AND FRGA-F) COMPARED AGAINST OTHERS LIKE FA [19], PF [8], MATFLOW [20], LGTV1 [21], IVT [22], MIL [23], PTP [24] AND BDF [20] ON SEQUENCES BALL, FERNANDO, GYMNASTICS, JOGGING, POLAR BEAR, SPHERE AND SURFING FROM VOT2014 DATASET. BEST, SECOND BEST AND THIRD BEST ARE HIGHLIGHTED IN RED, BLUE AND GREEN COLOR RESPECTIVELY.

| Tracker | FRGA-FB | | FRGA-F | | FA | | PF | | MatFlow | | LGTv1 | | IVT | | MIL | | PTp | | BDF | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sequences | A | FR | A | FR | A | FR | A | FR | A | FR | A | FR | A | FR | A | FR | A | FR | A | FR |
| ball | 0.76 | 0.0 | 0.76 | 0.0 | 0.83 | 0.0 | 0.70 | 0.0 | 0.64 | 0.0 | 0.32 | 1.2 | 0.33 | 4.0 | 0.45 | 0.8 | 0.44 | 0.0 | 0.51 | 2.0 |
| fernando | 0.40 | 1.4 | 0.39 | 2.6 | 0.39 | 0.0 | 0.39 | 1.8 | 0.33 | 0.0 | 0.46 | 0.2 | 0.39 | 3.0 | 0.46 | 2.0 | 0.30 | 4.0 | 0.42 | 1.0 |
| gymnastics | 0.64 | 0.6 | 0.60 | 1.0 | 0.58 | 1.0 | 0.56 | 1.0 | 0.54 | 2.0 | 0.49 | 1.0 | 0.56 | 4.0 | 0.26 | 4.6 | 0.37 | 1.0 | 0.57 | 1.0 |
| jogging | 0.73 | 1.0 | 0.44 | 0.4 | 0.55 | 0.6 | 0.38 | 2.0 | 0.71 | 1.0 | 0.38 | 1.0 | 0.72 | 2.0 | 0.20 | 1.0 | 0.62 | 1.0 | 0.75 | 2.0 |
| polar bear | 0.73 | 0.0 | 0.48 | 0.0 | 0.50 | 0.0 | 0.42 | 1.2 | 0.53 | 0.0 | 0.64 | 0.0 | 0.45 | 0.0 | 0.46 | 0.0 | 0.57 | 0.0 | 0.53 | 0.0 |
| sphere | 0.41 | 0.0 | 0.30 | 0.0 | 0.26 | 0.0 | 0.26 | 2.0 | 0.36 | 0.0 | 0.66 | 0.0 | 0.38 | 0.0 | 0.56 | 0.0 | 0.60 | 0.0 | 0.36 | 0.0 |
| surfing | 0.65 | 0.0 | 0.55 | 0.4 | 0.67 | 0.0 | 0.46 | 1.0 | 0.49 | 0.0 | 0.55 | 0.0 | 0.68 | 0.0 | 0.37 | 0.0 | 0.71 | 0.0 | 0.49 | 0.0 |

etc. These can be incorporated with the present framework for better object localization. We believe that each swarm based strategy exhibits its own strength in particular situations. Thus, a second direction can be explored to construct an ensemble of operations as a situation dependent combination of different strategies.

## REFERENCES


[1] D. Comaniciu, V. Ramesh, and P. Meer, "Kernel-based object tracking," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 25, no. 5, pp. 564–577, 2003.

[2] C. Yang, R. Duraiswami, and L. Davis, "Fast multiple object tracking via a hierarchical particle filter," in *Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on*, vol. 1. IEEE, 2005, pp. 212–219.

[3] C. Bao, Y. Wu, H. Ling, and H. Ji, "Real time robust l1 tracker using accelerated proximal gradient approach," in *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*. IEEE, 2012, pp. 1830–1837.

[4] V. Takala and M. Pietikainen, "Multi-object tracking using color, texture and motion," in *Computer Vision and Pattern Recognition, 2007. CVPR'07. IEEE Conference on*. IEEE, 2007, pp. 1–7.

[5] H. Zhou, Y. Yuan, and C. Shi, "Object tracking using sift features and mean shift," *Computer vision and image understanding*, vol. 113, no. 3, pp. 345–352, 2009.

[6] D. Comaniciu, V. Ramesh, and P. Meer, "Real-time tracking of non-rigid objects using mean shift," in *Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on*, vol. 2. IEEE, 2000, pp. 142–149.

[7] A. Yilmaz, O. Javed, and M. Shah, "Object tracking: A survey," *Acm computing surveys (CSUR)*, vol. 38, no. 4, p. 13, 2006.

[8] L. Marchetti, G. Grisetti, and L. Iocchi, "A comparative analysis of particle filter based localization methods," in *Robot Soccer World Cup*. Springer, 2006, pp. 442–449.

[9] K.-S. Tang, K.-F. Man, S. Kwong, and Q. He, "Genetic algorithms and their applications," *IEEE signal processing magazine*, vol. 13, no. 6, pp. 22–37, 1996.

[10] Y. Shi *et al.*, "Particle swarm optimization: developments, applications and resources," in *evolutionary computation, 2001. Proceedings of the 2001 Congress on*, vol. 1. IEEE, 2001, pp. 81–86.

[11] X.-S. Yang and X. He, "Firefly algorithm: recent advances and applications," *International Journal of Swarm Intelligence*, vol. 1, no. 1, pp. 36–50, 2013.

[12] M. Settles and T. Soule, "Breeding swarms: a ga/pso hybrid," in *Proceedings of the 7th annual conference on Genetic and evolutionary computation*. ACM, 2005, pp. 161–168.

[13] R. Thangaraj, M. Pant, A. Abraham, and P. Bouvry, "Particle swarm optimization: hybridization perspectives and experimental illustrations," *Applied Mathematics and Computation*, vol. 217, no. 12, pp. 5208–5226, 2011.

[14] K. Deb, A. Anand, and D. Joshi, "A computationally efficient evolutionary algorithm for real-parameter optimization," *Evolutionary computation*, vol. 10, no. 4, pp. 371–395, 2002.

[15] M. Kristan, J. Matas, A. Leonardis, T. Vojir, R. Pflugfelder, G. Fernandez, G. Nebehay, F. Porikli, and L. Čehovin, "A novel performance evaluation methodology for single-target trackers," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 11, pp. 2137–2155, Nov 2016.

[16] X. S. Yang, *Nature-Inspired Metaheuristic Algorithms*. Luniver Press, UK, 2008.

[17] X.-S. Yang, "Firefly algorithms for multimodal optimization," in *International symposium on stochastic algorithms*. Springer, 2009, pp. 169–178.

[18] A. K. Qin, V. L. Huang, and P. N. Suganthan, "Differential evolution algorithm with strategy adaptation for global numerical optimization," *IEEE transactions on Evolutionary Computation*, vol. 13, no. 2, pp. 398–417, 2009.

[19] M.-L. Gao, X.-H. He, D.-S. Luo, J. Jiang, and Q.-Z. Teng, "Object tracking using firefly algorithm," *IET Computer Vision*, vol. 7, no. 4, pp. 227–237, 2013.

[20] M. E. Maresca and A. Petrosino, "Clustering local motion estimates for robust and efficient object tracking." in *ECCV Workshops (2)*, 2014, pp. 244–253.

[21] L. Cehovin, M. Kristan, and A. Leonardis, "Robust visual tracking using an adaptive coupled-layer visual model," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 4, pp. 941–953, 2013.

[22] S. Zhang, H. Yao, H. Zhou, X. Sun, and S. Liu, "Robust visual tracking based on online learning sparse representation," *Neurocomputing*, vol. 100, pp. 31–40, 2013.

[23] B. Babenko, M.-H. Yang, and S. Belongie, "Robust object tracking with online multiple instance learning," *IEEE transactions on pattern analysis and machine intelligence*, vol. 33, no. 8, pp. 1619–1632, 2011.

[24] S. Duffner and C. Garcia, "Pixeltrack: a fast adaptive algorithm for tracking non-rigid objects," in *Proceedings of the IEEE international conference on computer vision*, 2013, pp. 2480–2487.