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Original Article

Tracking of player in volleyball sports using a metaheuristic algorithm

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Abstract:
Object Tracking is a thirsty region in the field of computer vision. Object tracking algorithms have greater priority because of the availability of highly facilitated computers, good quality and low cost cameras. Various researches are still carried out in this field, but it is nevertheless difficult to overcome a few drawbacks of object tracking. The challenges in object tracking involve occlusion, change of pattern appearance in both the scene and the object, poor images, changes in scene illumination, complex object movements, shape of the object etc. The current tracking algorithms also involve more mathematical complexity too. This research focuses on tracking of volley ball players playing in a test session. The videos are captured using high resolution camera. The video are captured when the players are under test session. The players are at first detected from the video frames using Cuckoo Search algorithm. The shadow that is present in the video frames is removed by segregating the pixel of the object and the pixel of shadow and normalized the RGB values and multiplied with matrix. Later, the value of the threshold is compared with the output and the shadow is segregated with reference to this threshold value. Then, the players are tracked by using three different metaheuristic algorithms such as Firefly, Cuckoo Search and Bat algorithms. The performance of the algorithms was compared against four measuring parameters such as Correct Detected Track, Latency in Track, Track Matching Error and Track Completeness. TMET and TCM are very important parameters among this. The result shows that TMET is less than 10.51 and TCM is maximum 0.85 for Bat algorithm. Thus, Bat algorithm found to be outperforming well in tracking the players from the video frames.
Keywords: Bat, Cuckoo Search, Firefly Algorithm, Player Detection, Player Tracking

Introduction

An analysis of sports video is quite an interesting field which in turn attracts many researchers for many applications. But the tracking of moving players is really a challenging task. Because in sports, the players may do some abrupt movements and they may have body articulations extensively, which may result in rapid changes in the appearance and the blurring of motion. This drawback impacts the most of the researchers to overcome the challenges in tracking the players from video sequences. Volleyball is a game in which the player makes jump and complex displacements. The classification of various shots played in the game is one of the primary areas of sports video analysis. The physical behavior and the temporal aspects are not been investigated yet due to the role and phase of competition (Yago et al., 2021). Vertical jump is an important key for any volleyball players so the players used to practice frequently this movement in the field (Daniel et al., 2021). So, our focuses on tracking the volleyball player in test session especially while they perform the vertical jump to hit the ball. In this research, we focused on tracking of volley ball players who are under test session. We have tracked the booster position of the player because this position is a very key position in the volley ball sports. This position is also the highlighting portion in volley sports. In this attacker position, the players will have an abrupt change in the motion of bodies while attacking the ball. So the tracking of this kind of abrupt changes in players in the challenging task in this research is important.In any tracking methods, the primary step is the object detection. All tracking algorithms are necessary to detect the object of interest either from the first frame or in every frame of the video. The traditional methods like background subtraction are available for the detection of objects from the video frames. But this method is not efficient in removing the noises [Archana et al., 2015]. This paper uses a Metaheuristic algorithm for detecting the player.

Object detection is still a difficult one because of a large number of mathematical computations in real time. This difficulty can be optimized using the Metaheuristic algorithms. The Metaheuristic algorithm makes this difficult task simpler using only a limited number of computations. The Metaheuristic algorithm can be applied to wider problems through its heuristic approach. It is a framework which can be used to solve various optimization problems with fewest changes applied for a specific problems. These algorithms consume less time

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to obtain the optimal solution [Xin-She et al., 2011]. After the object detection, object tracking is carried out. Tracking is defined as the estimation of objecttrajectory in the image plane which moves around in a scene [Y. Alper et al., 2006]. Tracking of a volley ball player provides useful information in analyzing the performance of the player. The ability of a player can be observed while they are doing their test session. Hence, in this research, this research helps the trainer to analyze the performance of the player, especially for the team selection.

Related Works

In the research they used Kalman filter for tracking of the ball. The ball is rolled over from top to bottom, and it is tracked while moving down. They used segmentation and detection technique to track the ball (Abdelali et al., 2016). But this paper has a drawback—when the ball of different colours is in it this technique will not be suitable for it. In another paper, they used Kalman filter and the probability product kernel to get the image region using a histogram that is more similar to the histogram of the tracked object (A. Salhi et al., 2020). But using this method may cause increase the noise in the background. So this method is not suitable when there is dense background at the video frames. In a research, they introduced the algorithm of Kalman filter for detection and tracking of multi-objects. To track the objects, they made some calculation of parameters to determine using Kalman filter (K. Yoon et al., 2018). But they used only 20 frames per second, which is suitable for this algorithm to perform the tracking in less time. In a paper they applied Multiple Hypothesis Tracking (MHT) algorithm for Multi-target multi camera tracking. They created a tree for track hypothesis, the branch of trees represent the track of a multi-camera and the target trajectory (Z. Wang et al., 2019). This system can solve the problem in real time and online but only if the single camera tracker is also solved in the same condition.

In a paper, they proposed a MHT integrated with the detecting process. MHT predicts the information of the location, and the adaptive threshold is calculated using this information. The tracks surviving are clustered, and each cluster's global hypothesis is calculated. The tracks which survived after pruning are taken for the next step (M.M.Naushad Ali et al., 2013). This algorithm minimizes the false alarm tracks, but it consumes more time. In a research, multiple humans are tracked from video frames only for partially occlusion. The human is detected using frame difference method and performed the operation of morphology. The Haris Corner algorithm is used to determine the feature points of each person. Histogram of Oriented Gaussian is determined for each feature, and these feature points are tracked using Particle filter (H. Chu et al., 2018). But this work gives the solution only for partially occluded objects, and it is not suitable for fully occluded objects. By combining the particle filter and convolution network, the target tracking algorithm is proposed in a paper. The features extracted using convolution and it is given to the frame work of the particle filter. The sparse representation is used to indicate the target block. The template is updated in the process of tracking (A. Vatavu et al., 2015). This paper has also given the better solution only for partial occlusion and not for full occlusion. A paper proposed a stereo vision method for tracking multiple objects in traffic scenarios of urban areas (M. Fang et al., 2014). But this system failed to optimize the processing time.

In another method, they proposed a tracking of a player in tennis videos which uses an adaptive Kalman filter. The filter parameters are adjusted depending on the player's detection, which in turn improves the accuracy of tracking using the correction of detection errors (D. Devikanniga et al., 2019). But this method got good average success for singles and less for doubles.Metaheuristic algorithms help to increase the efficiency by obtaining faster convergence using lesser iterations [Roxana et al., 2015]. Metaheuristic algorithms can provide better exploitation during the process of searching. These Metaheuristic algorithms are best suited for the problems having more unknown search spaces . Especially the algorithms inspired frame nature known as swarm intelligence becoming popular because of its flexible, versatile and simplicity. In a work, they proposed a method for tracking of optimal location using Metaheuristic algorithm (Djamel et al., 2018). Bat algorithm is well suited for their work for updating the equations of correlation filter in order to improve the accuracy of tracking.

The existing algorithm for tracking such as Kalman filter, Multiple Hypothesis Tracking, Particle Filtering has the challenges like occlusion, background noise, colour variations, higher latency etc. The researchers are still working on this tracking to overcome this drawback. To the best of our knowledge, no research work focused on tracking of volleyball players using a Metaheuristic algorithm. Generally, it is very difficult to track the players from video frames since the players will have complex position in video frames. This type of tracking sports players will involve lots of drawbacks as said above when using above-mentioned conventional algorithms. Hence, we have used this algorithm for tracking of volleyball players which involves more challenging positions of the player in video frames.

Proposed Method

In this research, the video has been captured using Canon 700d 5184 x 3456 pixels static video camera in the outdoor environment and in a day-light condition. The video was captured when the player was under test session. We hereby track 5 players while they are training to attack the ball to the opponent. This research uses three different metaheuristic algorithms to track the players. The following are the metaheuristic algorithms used for the tracking.

1. Firefly Algorithm
2. Cuckoo Search Algorithm
3. Bat Algorithm

The researchers faced various challenges in tracking the players because of various factors such as illumination variation of sunlight, shadow of the player, occlusion with the background objects like trees, light tower, pedestrians etc. The steps involved in the proposed work are shown in Fig. 1.

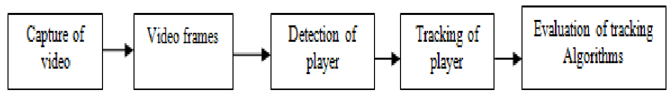


Figure 1. Block diagram of Proposed System

Object Detection

Object detection in videos is still challenging due to various factors like poor illumination, dynamic background, poor images etc. These challenges hold the object detection a highly focused research area in the field of computer vision. The traditional methods in object detection use proximity based measures, statistical approaches, index based approaches etc., and they do not show the better results in the detection of data and behave like an outline (P. Jayanthi et al., 2016). Here we used the adaptive threshold based on cuckoo search algorithm.

Cuckoo Search Algorithm

This algorithm is based on parasitic behavior of cuckoo (X. S. Yang, 2009). Cuckoo lays eggs only once Cuckoos do not build the nest of their own, and hence they lay eggs in host nets. In general, the Cuckoo egg hatches before the other host eggs that are in the host nest, and it throws out the eggs that are non-hatched. The host bird sometimes discovers an alien egg using the probability of pa ε [0, 1]. It can either abandon the nest or throw away the host eggs. This behavior of cuckoo is used to solve many optimization problems. In the proposed method, the adaptive thresholding based cuckoo search algorithm is used to detect the players. The following are the steps involved in the cuckoo search algorithm.

1. Randomly, 'n' nests are selected.
2. Using levy flight equation, randomly select a cuckoo using equation 1 as shown below

$$X_{i\,(t+1)} = X_i(t) + \alpha\ X\ L \qquad (1)$$

where, i=1, 2, …..n

n= No. of nests
α = size of the step
L = Levy Distribution

3. F_c is the fitness function which is calculated using equation 2 as shown below:

$$f(x) = \sum_{k=1}^{k}\sum_{i=1}^{n_k} (X_i - C_k)^2 \qquad (2)$$

Where, Xi = Patterns of the cluster
K = No. of clusters
C_k = Centre for K^{th} cluster.

4. Calculate the fitness function F_n for the randomly selected nest.
5. Replace the fraction pa with new nest if Fc is lesser than F_n
6. Keep the best nests by calculating its fitness as shown in equation 3.

$$f\ (x) = \sum_{i=1}^{k} \sum_{j=1}^{L+N} ||\alpha\ (X_j\ ) - \alpha\ (W_i\ )||^2 \quad (3)$$

where,
L= Normal data
N= Negative data
K = No. of clusters
W_i = Cluster centre
α(X j) = Mapping of non- linear function

6. Retain the best nest based on the fitness value.
7. Best nest will be the cluster centre.

Object Detection using Adaptive thresholding with cuckoo search algorithm

The colour image or grey scale image is taken as the input for the adaptive thresholding methods. For each pixel in the image, the threshold value is computed. If the threshold value is greater than the pixel value, then the image is said to be a foreground image or else it is set to the background image (A. Yasir et al., 2019). This is the optimization problem for the adaptive threshold method to obtain the optimal threshold value. In this proposed system, the threshold value is optimized using Cuckoo Search algorithm. In this algorithm, evaluations of group fitness are carried out and an optimal threshold value is estimated. Later, the region segmentation is performed with the level set method. The level set methods are a framework for doing segmentation in the selected region. It uses statistical analysis for this using the level set tool. At last, the morphological operation is carried out to refine the segmentation.

Object Tracking

Object tracking is defined as the estimation of object trajectory in the image plane which moves around in a scene. In the proposed method, five different volley ball players are tracked. In this research, three different metaheuristic algorithms such as firefly, bat and cuckoo search algorithms are used to track the players. These algorithms require only fewer computations compared with the traditional method of tracking.

Firefly algorithm

This algorithm is developed by XinSheYang in 2009 (X. S. Yang, 2009). It resembles the behavior and characteristics of flashing. This method is framed based on the fact that the fireflies are unisexual and they have the potential to attract each other. The individual level of brightness is equivalent to their attractiveness. So, the lesser-brightness fireflies will migrate towards the brighter fireflies. This attraction is proportional to their brightness. Without the brightness, the fireflies will have random movement (A. Pranay Kate et al., 2018). The objective function is calculated by the brightness of the firefly.The following are the steps of firefly algorithm:

1. Initialize the population of firefly and the criterion for termination.
2. Evaluate all the fireflies for their fitness from objective function.
3. Update the light intensity of the firefly
4. If the best location is not determined, search the best attractive location.
5. Evaluate the new best solution that is obtained and update the intensity of light.
6. Rank the fireflies and the current best value.
7. Until the best solution is obtained, repeat the step 2 to step 6 or otherwise terminate if the iteration exceeds.

The objective function is defined by equation 4 as,

$$X = (X_1, X_2 \dots X_d)^T \qquad (4)$$

Let X_i is the initial population of firefly. The intensity of light I_i and X_i is obtained by $f(X_i)$.

Object Tracking Using Firefly Algorithm

The population of firefly Z_0 is initialized randomly with a size of population 20. The brightness of the fireflies is the objective function $bZ_0$and it can be represented using equation (5) as,

$$bZ_0 = bZ_i\ (0),\ (i = 1, \dots \dots \dots 20) \qquad (5)$$

The attraction $\beta_{ij}(\tau - 1)$ among the fireflies $Z_i(\tau - 1)$ and $Z_j(\tau - 1)$ is given using equation (6) as below:

$$\beta_{ij}(\tau - 1) = \frac{\beta_0}{1+\gamma r_{ij}^2(\tau-1)} \qquad (6)$$

$\beta_0$is the attraction when r=0,γ is the coefficient of light absorption, r_{ij} can be given using equation 7 as below:

$$r_{ij}(\tau - 1) = \|z_i\ \ (\tau - 1)\|_2 \qquad (7)$$

The new position $z_i\ (\tau)$ of i^th firefly is derived using net motion $Vz_i(\tau - 1)$.This is given by equation 8 & 9.

$$Vz_i(\tau - 1) = \sum_{j\epsilon J(\tau-1)} VZ_{ij}\ (\tau - 1) \qquad (8)$$

$$z_{new}^i(\tau - 1) = z_i(\tau - 1) + VZ_i(\tau - 1) \qquad (9)$$

Where, $z_{new}^i(\tau - 1)$, is the brightness value of new position. The best population from these new positions is selected to get the next generation of fireflies. The brightness of the fireflies defined using object localization confidence. The iteration terminates if the maximum generation reached else the maximum iteration is reached. Here the iteration is set as 100.

Object Tracking using Cuckoo Search Algorithm

At first step, we set the Cuckoo Search parameters. The parameters include number of nests (n), probability of discovering pa and the criteria to stop (M. Gao et al., 2015). Here n=25, the discovering probability pa=0.6 and the maximum iteration to terminate is 200.Initially, the locations of nests are found by the set of values that are assigned to all the decision variables randomly. This is shown in equation 10.

$$nest_{i,j}^{(0)} = round\,[x_{jmin} + rand\,(x_{jmax} - x_{jmin})] \qquad (10)$$

The above equation is used to find the initial value of value of i^{th} nest. rand is the random number between 0 and 1. X_{jmax} and X_{imax} are the minimum and maximum, values for j^{th}variable.The best nest is retained and all the other nests are replaced by new cuckoo eggs using Levy flight. This is shown in equation 11.

$$nest_i^{(t+1)} = nest_i^{(t)} + \alpha S(nest_{best}^{(t)})rand \qquad (11)$$

Where, α =step size parameter,

$nest_i^{(t)}$= current position of i^{th} nest and

$nest_{best}^{(t)}$ = best position of nest.

S= Random walk using Levy flight.

The alien egg is discovered using probability matrix. If the alien egg was found by the host bird, it can either abandon the nest or throw out the eggs away. The new nest is constructed using equation 12. If the egg develops up without been thrown then it is taken into consideration for next generation.

$$nest = x_{min} + (x_{max} - x_{min})\, rand \qquad (12)$$

Where, x_{min} is the minimum value of nest and rand is the random number between 0 and 1. The optimization gets terminated based on the following three conditions:

1. The fitness function f_{worst} is good.
2. The Euclidian distance worst and best solution is well kept below with certain threshold value.
3. Algorithm terminates when the maximum iteration is reached. Here it is taken as 200.
4. The first two criterions depend on the objective function. So Bhattacharya Co-efficient is used. When Bhattacharya Co-efficient is kept greater than 0.6, the better target is represented.

Bat Algorithm

This algorithm was proposed by Yang (X. S. Yang, 2010) in the year 2010 which is based on echolocation of micro-bats. This echolocation characterization of bats is given by the following rules:

[1] Bats generally use echolocation to know the distance and by magical way, they also know about the distance between background barriers and the prey.

[2] Bats fly in random manner at the position X_i and with the velocity V_i with the frequency of loudness be fixed for searching the prey. They can adjust the wavelength of the pulse emitted and the rate of emitted pulse automatically based on the proximity of the target.

[3] Assume that the loudness vary from a large A_0 (positive) to the minimum constant value A_{min}.

[4] Each bat at its velocity V_i^{t-1} and the position X_i^{t-1} can be defined in a d dimensional search space and they will be updated in the iterations. The new velocity and position ($V^t$and X^t) at the time step t is determined using the strategy of global search. It is given in equation 13-15.

$$f_i = f_{min} + (f_{max} - f_{min})\beta \qquad (13)$$

$$V_i^t = V_i^{t-1} + (X_i^t + X')f_i \qquad (14)$$

$$X_i^t = X_i^{t-1} + V_i^t \qquad (15)$$

Where X' is the current best solution after compared with all the n bats at the present iteration. $\beta \varepsilon$ (0,1) is the random vector of uniform distribution, f_{min} and f_{max} is the minimum and maximum fitness function respectively. The domain size of the problem decides the value of f_{min} and f_{max}.To do the local search, a solution is selected among the current best solutions and the new solution for the bats is generated using random local walk. It is given in equation 16.

$$X_{new} = X_{old} + \varepsilon A^t \qquad (16)$$

Where, X_{old} is the current solution, $A^t = < A_i^t >$ loudness average at time step t for all the bats and ε(0, 1) is the random number. If the target is found, the pulse rate r_i and the loudness A_i are to be updated to indicate the bat to increase the rate of pulse and reduce the loudness by equation 17.

$$r_i^{t+1} = r_i^0[1 - exp\ exp\ (-\gamma t),\ A_i^{t+1} = \omega A_i^t] \qquad (17)$$

Where ω is the frequency of pulse increasing co-efficient,$r_i^0$is the initial pulse rate and γ is the attuenuation of pulse amplitude co-efficient.

Object tracking using Bat Algorithm

If the player is identified for the image being searched and if there is other elements like tree, pedestrians, lamp tower, net are found in the randomly generated, and the aim of Bat algorithm is to identify the player correctly. The player is detected in the first frame. Then the state vector is initialized. The state vector is defined as X= (x, y, s) where s is the parameter to control the size of the objet and (x, y) are the pixel co-ordinates on target location. Then by means of dynamic model new candidate's state vectors are generated. Here, f_{min} and f_{max} values of state vectors are f_{max} = (20, 18, 1.5) and f_{min}= (-20, -20, 0.7). This paper is concerned with search performance, so we used kernel based spatial histogram as the observation model. Here the population size is chosen as 5 to 30 with each space 5.

Performance Evaluation

In this paper, we proposed the metrics which compare the Ground Truth to the output of tracking. Before discussing on evaluation parameters, it is essential to define the concepts of spatial and temporal overlap between tracks. These are needed for justifying the level of matching between System Truth (ST) and Ground Truth (GT) [F. Yin et al., 2007]. The overlapping level A (ST_i, GT_j) between ST_i and GT_j in a particular track is known as spatial overlap. It is shown in equation 18.

$$A(ST_{ik}, GT_{jk}) = \frac{Area\ (ST_{ik} \cap GT_{jk})}{Area\ (ST_{ik} \cup GT_{jk})} \qquad (18)$$

The frame span overlap between Ground Track j and System Track i is known as Temporal Overlap (TO). It is shown inequation19.

$$TO\left(ST_i\,,\,GT_j\right) = \begin{cases} TO_E - TO_S & TO_E > TO_S \\ 0, & TO_E \leq TO_S \end{cases} \qquad (19)$$

Where, TO_E is the least of indexes of last frames of two tracks and TO_S is the highest indexes of the first frame. The below equation 20 is the condition for Temporal Overlap criterion to associate GT and ST tacks.

$$\frac{Length\ (ST_i \cap GT_j)}{Length\ (ST_i \cup GT_j)} > TR_{ov} \quad (20)$$

Where, TR_{ov} is an arbitrary threshold and Length is the number of frames. If the above condition satisfied, then we can associate GT with ST tracks and later on we can evaluate the system track performance. Here we define the metrics as follows.

Correct Detected Track (CDT):

The following is the condition for GT track to be satisfied for the correct detection.

- The temporal overlap of system track i and ground track j should be greater than the predefined threshold of track overlap TR_{ov}. Here it is set as 20% as shown in equation 21.

$$\frac{Length\ (ST_i \cap GT_j)}{Length\ (ST_i \cup GT_j)} \geq TR_{ov} \qquad (21)$$

- There should be enough spatial overlap for system track i with ground truth track j. It is given in equation (22).

$$\frac{\sum_{K=1}^{N} A\,(ST_{ik}\,, A{=}GT_{jk})}{N} \geq T_{ov} \quad (22)$$

Based on the above conditions, all System tracks are compared with each GT track. At least more than one system track satisfy the above condition, the GT track is considered to be correctly detected. Therefore, if all GT tracks are correctly detected, then the True positive is equal to the number of GT tracks.

Latency of Tracking (LT)

Latency is otherwise known as time delay. It is the time interval between the appearance of the object for the first time and that object start tracked by the system. If there is larger latency which indicates that the system is insensitive to trigger the tracking in time. It can be calculated by the frame difference between the first frame belongs to GT and the first frame belongs to ST. It can be given using equation 23.

$$LT = First\ Frame\ of\ ST_i - First\ frame\ of\ GT_j \qquad (23)$$

Track Matching Error (TME)

It is the metric which measures the positional error of ST. It measures the average distance error between GT track and ST track. If TME is low which indicates the system track has the higher accuracy. It can be given using equation 24.

$$TME = \frac{\sum_{k=1}^{N} Distance\ (GTC_{jk}\,,\ STC_{ik})}{Length\ (GT_j \cap ST_i)} \qquad (24)$$

Where Dist ( ) is the Euclidean distance between centroid of ST and centroid of GT. Track Matching Error (TMEMT) for the entire video frames can be defined as the weighted average during the overlapping of each pair of tracks as co-efficient of tracks. It is given using equation 25.

$$TMEMT = \frac{\sum_{t=1}^{M} Length\ (GT_j \cap ST_i)_t\ X\ (TME)_t}{\sum_{t=1}^{M} Length\ (GT_j \cap ST_i)_t} \qquad (25)$$

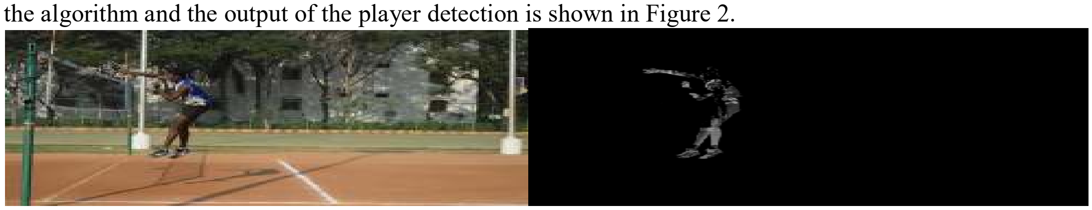
Track Completeness (TCM)

It can be defined as the time for which GT track overlapped with ST track divided by total duration of GT track. It is given using equation 26.

$$TMEMT = \frac{\sum_{t=1}^{M} Length\ (GT_j \cap ST_i)_t\ X\ (TME)_t}{\sum_{t=1}^{M} Length\ (GT_j \cap ST_i)_t} \qquad (26)$$

Results

The video has been captured using a static camera. First, it is subjected to conversion of frames. The first step is the player detection from video frames. Here we used Cuckoo Search Algorithm to detect the player. The input to the algorithm and the output of the player detection is shown in Figure 2.



(a) **(b)**

Figure 2 (a) Input for player detection (b) Output of player detection

While doing the player detection, we had the problem of shadows of the player, light towers, net etc. These shadows are similar to the foreground objects. So, to segregate the pixel of the object and the pixel of shadow, we normalized the RGB values and multiplied with matrix (H. Adesh et al., 2015). Later, the value of the threshold is compared with the output. If the value is greater than the value of the threshold, then it is calculated using equation 27.

$$L = GTx(116x\, Y^3 - 16) + (\sim GT)\ X\,(903.3\ x\ Y) \quad (27)$$

When L is lesser than the value of threshold, the output will be 0 and it is set as a shadow region; otherwise, it will be considered as a foreground object and the output is set to 1.
The tracking is made for 5 different players during the test session. The player attacks the ball in the attacker position, and the tracking is made until the ball is attacked by the player. The players are tracked in the attacker position as this position has a challenging task.

(a) **(b)** **(c)**

Figure 3. (a) Tracking output of Firefly (b) Tracking output of Cuckoo Search (c) Tracking output of Bat of Player 1 – Frame 16

(a) **(b)** **(c)**

Figure 4. (a) Tracking output of Firefly (b) Tracking output of Cuckoo Search (c) Tracking output of Bat of Player 2 – Frame 76

(a) **(b)** **(c)**

Figure 5.(a) Tracking output of Firefly (b) Tracking output of Cuckoo Search (c) Tracking output of Bat of Player 3 – Frame 58

(a) **(b)** **(c)**

Figure6. (a) Tracking output of Firefly (b) Tracking output of Cuckoo Search (c) Tracking output of Bat of Player 4 – Frame 92

(a) **(b)** **(c)**

Figure 7.(a) Tracking output of Firefly (b) Tracking output of Cuckoo Search (c) Tracking output of Bat of Player 5 – Frame 61

But using a Metaheuristic algorithm, we tracked almost precisely the different positions of the players and we could also be able to track the players even when they were moving fast. This position helps in analyzing the real capability of the players and which in turn helps the trainer to choose the best player for the team. From the above figures 3 to 7, by looking at the square blobs in each algorithm, we can say that the Bat algorithm has performed well in tracking the players in different positions. But however, we have analyzed these different Metaheuristic algorithms against various performance parameters for each player.

Discussion

The Table 1-5 given below presents the results of performance metrics. It is observed from the table that higher metric CDT shows that the Bat algorithm outperforms well in most of the video sequences. Only for Player 3 and Player 4 video sequences Cuckoo Search outperforms well. Here a very important parameter is TMET since it indicates the accuracy of the system track. The TMEMT should be as low as possible. Here from Table 1 – 4 it is observed that the TMEMT is low value for Bat algorithm mostly.

In general, TCM should be higher for a good tracking. Here from the table it is observed that TCM has lesser value for the Firefly algorithm and higher value for Cuckoo Search and Bat Algorithm. Latency also shows better for Bat algorithm than other two algorithms. So overall, Bat algorithm has outperforms well in most of the parameter metrics.

Table 1. Comparison of Algorithms against CDT, LT, TME and TCM for Player 1

Parameters	FFA	CSA	BA
CDT	1	4	5
LT	10	7	5
TMEMT	11.25	12.52	10.09
TCM	0.87	0.71	0.42

Table 2. Comparison of Algorithms against CDT, LT, TME and TCM for Player 2

Parameters	FFA	CSA	BA
CDT	4	6	7
LT	12	10	9
TMEMT	11.04	9.09	7.05
TCM	0.57	0.67	0.74

Table 3. Comparison of Algorithms against CDT, LT, TME and TCM for Player 3

Parameters	FFA	CSA	BA
CDT	2	6	5
LT	15	12	10
TMEMT	15.14	12.05	10.51
TCM	0.74	0.48	0.52

Table 4. Comparison of Algorithms against CDT, LT, TME and TCM for Player 4

Parameters	FFA	CSA	BA
CDT	1	4	3
LT	14	11	12
TMEMT	11.05	10.15	9.05
TCM	0.67	0.74	0.85

Table 5. Comparison of Algorithms against CDT, LT, TME and TCM for Player 5

Parameters	FFA	CSA	BA
CDT	2	3	5
LT	13	14	11
TMEMT	12.42	9.07	10.08
TCM	0.43	0.53	0.62

Conclusion

In this paper, the video has been captured when the players are attacking the ball to the opponent during a test session. Later the players are detected in the video frames using Cuckoo Search Algorithm. This involves detection of players as foreground images and removal of the background images. After detecting the players, they have been tracked over the entire video sequence using a metaheuristic algorithm, and these tracking are compared against the various parameter metrics. Here four different parameters are taken for the measurement of the performance of the tracking algorithm. Bat algorithm outperforms well in Latency, CDT, LT, TMET and TCM parameters. Thus we conclude that Bat algorithm, can track the player in all the frames and this algorithm is best suited for this application on comparison with the other two algorithms. This work can enhance further by carrying out the measuring of the various performances of players which can help the trainers to select the players for their team.

Conflicts of Interest – The author declares no conflict of interest

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