A Comprehensive Survey on Evolutionary Algorithm based Object Tracking Techniques

A. Nirmala[1], Dr. S. Arivalagan[2], Dr. S. Mohan[3]

[1]*Research Scholar, Department of Computer Science, Annamalai University*

[2,3]*Assistant Professor, Department of Computer Science & Engineering, Annamalai University*

[1]sjcnirmala@gmail.com

[2]arivucseau@gmail.com

[3]mohancseau@gmail.com

***Abstract*— Presently, visual tracking become more popular in the area of computer vision. For effective object tracking, the tracking method should have the capability to separate the target object from background accurately. While designing the model of visual tracking, several issues need to be considered. Some of the issues are occlusion, scale variation, rotation, motion blur, deformation and background clutter. In order to achieve effective visual tracking, numerous visual tracking methods are developed. After bio-inspired algorithms come into the lime light for solving combinatorial optimization problems, visual tracking grasps a number of researchers for solving it. This part of interest leads the researchers to produce many algorithms for visual tracking along with hybrid models for efficient tracking process. This paper reviews the existing evolutionary algorithms (EAs) based visual tracking methods for proper object tracking. The existing methods are reviewed based on their aim, underlying methodology, performance measure, advantages and its limitations.**

***Keywords*—** Visual tracking, Evolutionary algorithms, swarm intelligence, particle swarm optimization

I. Introduction

Recently, the concept of visual tracking plays a significant part in computer vision [1]. Many researchers are carried out in visual tracking because of several practical applications. It is widely used from military applications to civilian applications like border surveillance, object tracking, behavior analysis, Human Computer Interaction (HCI), etc. [2]. The difficulty of the tracking system based on various factors like information known earlier about the target object and number of parameters monitored (location, scale). Existing tracking methods works well and produce effective results only in simpler situations, i.e. slow motion, less occlusion, etc [3]. Tracking generic objects is still a difficult due to the presence of blur, rotation, fast motion, occlusion, scale variation, pose change and background noise. These challenges are illustrated in Fig. 1. So, a new effective tracking model is needed to solve these issues. A traditional tracking model comprises of three units: appearance, motion and search strategy models [4]. The appearance type calculates the probability of the object of interest at some specific location. The second model interconnects the location of the object with respect to time. The third model finds the more appropriate location of the object in the current frame. An appearance modeling is used to develop a mathematical model for the identification of objects, especially in visual tracking [5]. Generally, there are two types of trackers which include generative tracker and discriminative trackers. The former trackers find the target which looks same as target object. This method uses templates, subspace or inference methods. Discriminative tracking method uses binary classification problem to differentiate the target from the background.

The tracking methods can also be classified into two methods with respect to representation mode. The two methods are holistic method and parts-based method. The holistic method captures larger objects by mapping the appearance of the target with global cues [6-8]. For local visual cues, holistic method fails to produce better results. On the other side, parts -based method mapped the target appearance with local patches, which encodes the spatial information. These patches are not connected tightly to some extent of spatial deformation. This method can be used for short term tracking and produces better results than holistic method. This method works well in presence of partial occlusion. Due to non-consideration of the entire information of the object, it fails to track objects in the existence of background clutter and motion blur. It is clear that both holistic and parts based method considers only a part of visual cues, either global or local cues. These methods use the information within the object and ignoring the textual cues. The existing tracking methods fail to produce effective results in complicated situations.

Though single tracking models are computationally less complex, it is not suitable for situations with occlusion and noise. Multi-object tracking approaches manage occlusion in an effective way by the use of high level associations. Multi-object tracking methods are computationally more complex than single tracking method. For visually tracking the object in complicated situations, evolutionary algorithms (EAs) based visual tracking methods for proper object tracking are proposed. This paper reviews the existing methodologies based on their aim, underlying methodology, performance measure, advantages and its limitations. A detailed comparison of the reviewed techniques is also made.

Fig.1 Difficulties present n tracking in real word, occlusion (woman), abrupt motion (shaking), illumination change (car Dark), pose variation (Bird) and complex background (board).

The rest of the paper is arranged as follows. The traditional tracking methods are discussed in Section 2 and the EA based visual tracking methods are reviewed in Section 3. In Section 4, conclusion is given.

II. Classical Tracking Approaches

In the last decade, numerous models are proposed in the area of target tracking. For the sake of simplicity, some of the traditional existing models are discussed. Feature extraction is the important task in tracking process. The tracking models can be classified to holistic approach and local-based approaches. Holistic approach considers that the target is stable in successive frames. Some researchers showed that this method performs well due to its simpler representation. An appearance model is presented to adaptively select the color features [15].

This method can easily differentiate the target from its background. An online Hough-based method is presented for tracking non-rigid objects [16]. To track non-rigid objects, [17] proposes a method to identify the target object by reducing the Bhattacharyya distance from the color histograms of reference model and target bounding boxes. An online appearance modeling technique is developed by the utilization of sequential density approximation [18].

Another online method is proposed [19] to discriminate the target object by filtering the background by training a discriminative classifier. During training, the tracking result is considered as positive sample and surrounded bounded boxes are considered as negative samples. But, these methods can be easily affected by the presence of noise. Based on correlation filters, a fast tracking method [20] is proposed in a latest benchmark (OTB) [21]. This method does not consider the factor of online model updating. This method is fails to achieve poor tracking results in presence of occlusion for a longer time. In recent days, visual saliency is employed to attain accurate results because of its better performance in object detection [22]. Computational complexity is the major drawback of visual saliency. It is clear that holistic methods is capable of acquiring larger size images but fails to adapt the appearance variations in presence of occlusion and deformation.

Parts-based approach produces better results in the existence of occlusion and deformation [23-25]. In some partially occluded situations, the rest of the visible part is capable of providing reliable cues for tracking. A star like appearance model [26] is proposed to improve the tracking accuracy and robustness using segmentation techniques. A new method is developed to present the structural information among the interior parts of the target. A graph-matching method is used to interconnect the adjacent frames. This method performs well in the existence of occlusion and deformation. A part based algorithm [27] is developed to investigate the interconnection between the whole object and local patches. They used two-stage training process to identify the target position. A discriminative ranking list based tracker is presented to restrain the distractor [28]. In this method, the target is represented by the patches of smaller and larger sizes. Smaller patches are employed to calculate the confidence of every individual input patch and larger patches are utilized to eliminate the untrustworthy smaller patches. [29] splits the bounding box into several patches and it chose only the significant patches to produce a precise foreground probability map. Most of the reviewed approaches are slower in producing results in benchmark (OTB). To eliminate this drawback, a novel tracking approach is proposed for tracking objects using multiple correlation filters [30]. It produces accurate tracking and robust in the presence of occlusion and deformation. Several approaches uses local patch to track the objects. For enhancing the tracking performance, background information is combined with the tracking models. A couple layer model [31] is proposed which represents the target by the combination of local and global appearance.

III. EA Based Tracking Approaches

In this section, various recently proposed EA based tracking approaches are discussed in detail. Some of the popular EA algorithms employed in visual tracking are particle swarm optimization (PSO), genetic algorithm (GA), bat algorithm, firefly (FF) algorithm, harmony search (HS), bat algorithm (BA) and so on. From the earlier studies, variants of PSO algorithm are devised and successfully employed for visual tracking. A comparison of the reviewed methods is tabulated in Table 1.

In [32], the author presented a PSO based object tracking algorithm for image sequences. At the initialization of every frame, the particles are drawn from a Gaussian distribution to cover up the significant object locations and then PSO algorithm will be executed to focus the particles in the vicinity of the centre of the object template. Using this method, the resampling step is eliminated. The main intention of PSO algorithm is to transfer the particles move towards significant areas in the search space. To evaluate the particle score, a grayscale appearance model that is learned on-line is employed and a set of image sequences such as Foreman, Caviar and Carphone are used. The simulation results verified that the proposed PSO based visual tracking is found to be feasible particularly in presence of rapid motion or the appearance modifications are considered.

Due to dynamic behavior of object tracking problem based on the object state and time, a sequential PSO (SPSO) algorithm is proposed in [33], which integrates the temporal continuity information to the conventional PSO algorithm. Additionally, the variables in PSO are modified dynamically based on the fitness value of the particles and the predicted motion of the tracked object, resulted to a constructive performance in tracking applications. Besides, it is showed in a theoretical manner that, in a Bayesian inference perspective, the PSO iterations are basically a swarm-intelligence based multi-layer importance sampling methodology which integrates the new observations to a sampling level and it eliminates the issue of sample impoverishment by the particle filter. A series of experiments is done and the results of the SPSO are compared with original particle filter (PF) and unscented PF (UPF) on a video with manually labeled ground truth.

The experimental results depicted that the proposed SPSO algorithm performs well than the state of art methods interms of MSE. The authors in [34] presented an EA based tracking method named as IS_ObjTrack which uses PSO algorithm which is robust and faster. The benefit of the IS-OBjTrack is the use of histogram of oriented gradients (HOG) in the design of object appearance design. The HOG based appearance model is voluntarily used by PSO for fastness. The HOG comes under the group of gradient based filters, which shows better performance for the objects with discriminate edges. The appearance model is planned in such a way that it is adaptable; thereby the parameters are updated in online. The efficiency of the IS_ObjTrack is validated by comparing its results with SWF method. These methods are applied to different videos of faces and cars. As HOG comes from the group of gradient based filters, the tracker is adaptable for the objects with distinct edges like a human body or a vehicle. Using the three dataset Dudek-Toronto, MIT-CBCL and a generic car video, the PSO based IS_ObjTrack method is found to be superior to SWF method interms of RMSE.

A multi-target tracking algorithm based on PSO algorithm is devised in [35]. In the starting of every frame, the target objects are tracked separately by the use of highly discriminative appearance models among diverse targets. Every individual target is being tracked using separate PSO algorithms. The target positions and velocities which are computed by independent trackers are further applied in PSO based methodology, which refine the trajectories filtered in the earlier phase. Next, a conjugate methodology is employed in the final optimization. Moreover, a complex energy function is employed to represent the existence, motion and interaction of all targets inside a temporal window comprising of the latest frames. Using two publicly available, dataset, this algorithm is compared with the standard PSO algorithm in a quantitative way. From the result analysis, it is depicted that the proposed algorithm is found to be better than the related methods.

Generally, the robust tracking of random objects needs high processing power. This tracking of objects in day to day life introduces delay in the tracking system. For increasing the speed of the process, PSO algorithm is used for tracking [36]. This algorithm enables the system to track the objects with less hardware needs. The output from PSO algorithm generally holds less noise. For eliminating noise and computation of trajectory of the object, Kalman filter is used. The Kalman Filter algorithm is an asymptotic state estimator for various dimensions. It performs prediction of upcoming state of the model depending upon the past states. This filter is used to filter the output created by PSO and also to compute the trajectory of the object. For testing the goodness of the proposed algorithm, it is applied under dynamic conditions on different systems with varying OS platforms. In addition, the proposed algorithm employs PSO algorithm, the proposed method does not generates any delay.

[37] presented a new object tracking method using Dominant points on tracked objects by the use of Quantum particle swarm optimization (QPSO) algorithm. The fascinating characteristic of the proposed method is the nature of adaptability to variable background as well as static background. The application of QPSO is found to be faster whereas the traditional PSO algorithms have high computational complexity. In the beginning, the dominants points of tracked objects are identified and then a collection of particle create a swarm undergo random initialization over the image search space and then begins search process of the curvature linked among two successive dominant points till it satisfies the fitness condition. The simulation results verified that the proposed QPSO based tracking algorithm works well in visual object tracking in both dynamic as well as static platforms. Interms of runtime, it is found to be 90% faster than basic PSO algorithm.

[38] presented a visual tracking method to study the intelligence nature of fishes which is observed in the experiments by catching fish for a manipulator real-time visual servoing. This visual tracking system uses the global search feature of a GA as well as local search methodology of the GA. The unprocessed raw grayscale image is employed for the detection of a recognized target object being imaged. In addition, the determination of fitness function in GA is depending upon the configuration of an object model elected as surface-strips model. The raw images are employed as it is highly tolerable to the contrast changes from an input image to the subsequent. Furthermore, it does not need any time for filtering processing, which is helpful for recognizing objects in real time. The global GA procedure is used with the local GA for recognizing the target shape and identifies the position and orientation concurrently, and to enhance the GA’s convergence speed to attain quicker and good recognition performance. For experimentation, a hand eye camera is used to track the fish and manipulator is used to catch the fish with a net attached at hand of the manipulator. The accomplishment of catching fish ensures the efficiency of the proposed method for manipulator real-time visual servoing. By this study, the competitive behavior of the fish instinct to escape from net can be clearly observed. A harmony filter based on HS algorithm is presented in [39] for visual tracking. The proposed harmony filter defines the target as a color histogram and looks for the best computed target location by the use of Bhattacharyya coefficient as fitness metric. The simulation results verified that the proposed filter can efficiently tracks the random target even in harsh environments. The performance of the harmony filter is compared with PF and UPF interms of speed and accuracy. The obtained values showed that the proposed filter is found to be faster and more accurate than the compared filters.

An FF algorithm-based tracking algorithm is introduced in [40] and the parameters' sensitivity and adjustment of FF algorithm in the tracking process FA in tracking model are analyzed. The experimentation results verified that is robust while tracking arbitrary targets in different challenging conditions. The proposed FF algorithm is compared with existing methods such as PF, mean shift and PSO algorithm. The implementation results depicted that FF algorithm is better than the existing ones. In [41], a new multiple object tracking based on optimization FF algorithm is introduced. FF algorithm contains some features like PSO algorithm with better performance in optimization problems. In this method, the similarities between primary objects window as well as secondary objects window in every frame is chosen as the objective function.

FSIM algorithm is employed to compute the similarities between two windows which are determined by FF algorithm. Finally, the issue of window location in every frame is identified by FF algorithm. The simulation results verified that the proposed FF with FSIM algorithm significantly enhances the tracking accuracy under various issues like occlusion, low quality, complex background and unanticipated movements. A set of videos from Indoor football, traffic camera and surveillance camera are used for validation. This paper employed the behavior of bats to search targets in a series of images. A BA-based tracking model [42] is introduced and the sensitivity as well as adjustment of the parameters in BA is investigated. For the validation of the tracking capability of the BA-tracker, PSO, PF and mean shift under different difficult examples are investigated.

Due to the limitation of existing EA based tracking methods such as pre-mature convergence, loss in particle information and insufficient feature are recognized since the factors that hold back the results of this level of trackers. To overcome the issue, a hybrid gravitational search algorithm (HGSA) is presented [43] to enhance the exploitation of particle information and to assist complete searching of the video frame in prior to convergence. The hybrid algorithm obtains the utilization of previous information and fast convergence characteristic of PSO, retains the GSA ability in fully utilizing all current information. Furthermore, the integration of deep convolution feature is presented to overcome the inefficiency of the HSV histogram feature. The simulation results depicted that the presented DeepHSA algorithm has enhanced accuracy than the other EAs.

TABLE I

COMPARISON OF DIFFERENT REVIEWED OBJECT TRACKING METHODS

References	Aim	Algorithm	Measures	Test videos	Compared with
[32]	object tracking for image sequences	PSO	MSE	Foreman, Caviar and Carphone	PF
[33]	Address dynamic nature of object tracking	SPSO	MSE	video with manually labeled ground truth	PF, UPF
[34]	robust and fast-tracking algorithm	PSO and HOG	RMSE	Dudek-Toronto, MIT-CBCL and a generic car video	SWF
[35]	multi-target tracking	PSO	Quantitative way	publicly available, dataset	standard PSO
[36]	increase the speed of the tracking process	PSO and Kalman filter	delay	-	-
[37]	object tracking method using Dominant	QPSO	Run time	Static video is 20 sec duration	PSO
[38]	study the intelligence nature of fishes	GA	-	Hand eye camera fish images	-
[39]	Visual tracking	HS	Speed and accuracy	3 video sequences	PF, UPF
[40]	Visual tracking	FF	Accuracy	four indoor and outdoor videos	PF, mean shift and PSO
[41]	multiple object tracking	FF and FSIM	Accuracy	Indoor football, traffic camera and surveillance camera	-
[42]	to search targets in a series of images	BA	Cost	snapshots from video clips	PSO, PF and mean shift
[43]	to enhance the exploitation of particle information in the tracking process	HGSA	Accuracy	30 online benchmark videos	WAPSO, ADSO
[44]	multiple object tracking	Quad-CNN	Accuracy, precision, average number of false alarms per frame, Mostly Track targets	2DMOT2015 dataset	NOMT, TDAM, MHT-DAM, MDP, SCEA
[45]	Object tracking in complex backgrounds	DNN	Success rate, central-pixel error	8 video sequences	CT, DLT, IVT, MIL, MTT
[46]	online tracking	CNN+KCF	Qualitative way	OTB2013	CSK, DFT, MTT
[47]	online multi-object tracking	CNN	detection missing rate	MOT15	MDP, SORT
[48]	multi-object tracking	Deep network	cost function	KITTI tracking, MOT15 and MOT16	

IV. Neural Network Based Tracking Algorithms

A Quadruplet Convolutional Neural Networks (Quad-CNN) [44] for multi-object tracking is proposed which learns to integrate object identification among frames by the use of quadruplet losses. This method assumes target appearances together with their temporal adjacencies for data association. In contrast to traditional ranking losses, the quadruplet loss imposes an extra limitation which makes temporally adjacent identifications nearly placed than the one with larger temporal gaps. A multi-task loss is also employed to jointly learn object association and bounding box regression for effective localization. The entire network undergoes training process. For tracking, the target association is done by minimax label propagation by the use of measure metric learned from the proposed network. The Quad-CNN is evaluated using the publicly available MOT Challenge datasets, and the results depicted that the proposed network outshines than the compared ones.

Object tracking in complex backgrounds with dramatic appearance variations is a challenging problem in computer vision. We tackle this problem by a novel approach [45] that incorporates a deep learning architecture with an on-line AdaBoost framework. Inspired by its multi-level feature learning ability, a stacked denoising autoencoder (SDAE) is used to learn multi-level feature descriptors from a set of auxiliary images. Each layer of the SDAE, representing a different feature space, is subsequently transformed to a discriminative object/background deep neural network (DNN) classifier by adding a classification layer. By an on-line AdaBoost feature selection framework, the ensemble of the DNN classifiers is then updated on-line to robustly distinguish the target from the background. Experiments on an open tracking benchmark show promising results of the proposed tracker as compared with several state-of-the-art approaches.

The author presented an online tracking model [46] by the integration of shallow convolutional neural networks with kernelized correlation filters (KCF). From the variation of offline training, the proposed method efficiently achieves the convolution kernels using K-means clustering algorithm. using a visual tracker benchmark dataset, it is verified that the proposed work is efficient compared to other methods.

The author exploited the characteristics from many convolutional layers to present an online multi-object tracking (MOT) framework [47]. Particularly, the top layer is formulated as a category-level classifier and uses a lower layer to detect instances from one category with the assumption that the intuition that lower layers holds many information. To reduce the computation complexity of the online fine-tuning, the appearance model is trained with an offline learning mechanism by the use of the past appearance reserved for every object. The proposed method is validated by the use of MOT benchmark dataset to highlight the efficiency of the proposed method when compared to the other methods.

This paper presents the work for learning characteristics for network-flow-based data association using backpropagation [48], by expressing the optima of a smoothed network flow problem as a differentiable function of the pairwise association costs. The simulation results depicted that the proposed method successfully learns all cost functions for the association problem in an end-to-end fashion, which outperforms hand-crafted costs in all settings. The association of different sources of inputs became easier and the cost functions can be learned thoroughly from data, lessening difficult hand-designing of costs.

V. Conclusions

In real scenario, it is not easier to track the target objects in complex situations (presence of fast motion, occlusion, etc.). For effective visual tracking, the tracking method should have the capability to separate the target objects from the background accurately. For the sake of simplicity, some of the traditional existing models are discussed. In order to visually track the object in complicated situations, EA based visual tracking methods for proper object tracking are proposed. This paper reviews the existing methodologies based on their aim, underlying methodology, performance measure, advantages and its limitations. A detailed comparison of the reviewed techniques is also made.

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