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An Efficient Visual Tracking System Based on Extreme Learning Machine in the Defence and Military Sector

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ABSTRACT

Visual tracking is the capacity to estimate or forecast a target object's location in each frame of a video after specifying its starting position. Visual tracking is of essential relevance in defence and military operations. The military can use it to improve situational awareness, improve precise targeting, acquire intelligence in real-time, and efficiently respond to a variety of threats and circumstances. In the past, object tracking systems have relied mostly on algorithms based on deep learning techniques and these tracking algorithms are lacking in both accuracy and speed. In this research, an Extreme Learning Machine-based visual tracking system has been proposed that incorporates properties like high accuracy, low training time, and less network computing complexity as compared to existing deep learning-based tracking algorithms. The Haar wavelet transform is utilized in the recommended technique for feature learning, while the extreme learning machine is utilised for classification and recognition. A benchmark dataset object tracking benchmark-2013 has been used to carry out the experiments. The experiment values indicated that the proposed technique has accomplished enhanced performance over another tracking model. Additionally, we tested the proposed method's accuracy and robustness regarding certain visual characteristics: Illumination variation, occlusion, deformation, out-of-plane rotation, background clutters, and in-plane rotation. The findings of the simulation revealed that the objects in videos have been 84% accurately tracked by the suggested method.

Keywords: Discrete wavelet transform; Haar wavelet transform; Computer vision; Deep learning

NOMENCLATURE

ELM	: Extreme learning machine
OTB	: Object tracking benchmark
IV	: Illumination variation
OCC	: Occlusion
DEF	: Deformation
BC	: Background clutters
OPR	: Out-of-plane rotation
DL	: Deep learning
DWT	: Discrete wavelet transform
SLFN	: Single hidden layer feed forward neural networks
CLE	: Center location error

1. INTRODUCTION

Due to the recent advances in computer vision, video-based object-tracking algorithms have become an increasingly prevalent subject in academic institutions all over the world[1-2]. Human-based monitoring systems can no longer keep up with the ever-increasing demands placed on security in the modern day. Therefore, it is essential to seek out research and development of intelligent video tracking systems[3]. The technique of detecting a moving object or many moving objects throughout a certain amount of time using a camera is referred to as object tracking. To be more precise, Tracking is the process of determining the route or trajectory of an object in the image plane as it travels across a scene[4]. Object tracking is vital to defence and military applications because it improves situational awareness, permits accurate targeting, supports force protection, and is essential to many military missions, including crisis management and surveillance, and reconnaissance. It helps make military operations more successful and effective overall.

Although several algorithms have been presented over the past few decades based on deep learning methods, designing an effective and resilient tracker that can adapt to changes in appearance due to things like lighting, position, occlusion, background clutter, etc. is still a challenge. The majority of currently available tracking algorithms are determined to be unsatisfactory in both accuracy and speed. A good classification tracker should incorporate the following given characteristics: (1) low complexity, (2) quickly adapt to visual changes of foregrounds and backgrounds, and (3) powerful feature extraction method[5]. The extreme learning machine (ELM)[6-8] is a new development in the realm of neural networks that satisfies all of the aforementioned conditions.

In Deep Learning (DL), most of the algorithms are based on a gradient descent approach. This method requires tuning a lot of parameters, which makes longer training time, needs expensive hardware and the knowledge of experts,

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and sometimes has problems with "local minima," etc.[9-11]. In contrast, many researchers are now switching to ELM, which has advantages like faster convergence and learning without iterative tuning of parameters which results in lesser training time, higher accuracy, less user interaction, real-time learning, better generalisation performance, etc.[6,12-14]. In this work, an efficient visual tracking system based on discrete wavelet transform has been proposed, which is employed for feature learning and extreme learning machines that recognize and classify the target object in the videos and produce a prediction as to their future states.

To further illustrate how the suggested visual tracker works, several extreme learning machine-based and deep learning-based trackers have been examined. Miao[15], *et al.* suggested an ELM and HOG3D-based human motion recognition system with good performance straightforwardly. To ensure effective hardware acceleration, using a custom System-On-a-Chip (SoC) Field-Programmable Gate Array (FPGA) architecture, Safaei[16], *et al.* show how an ELM/OS-ELM may be built. Acceleration is achieved through a combination of factors, including parallel extraction, significant pipelining, and effective shared memory connection. To mine the similarity between the distribution of labeled data and unlabelled samples, Qiu[17], *et al.* suggested an online semi-supervised tracking approach that was based on an extreme learning machine. Using wearable sensors, Siu[18], *et al.* developed a method for sequentially recognizing human activities that are based on deep convolutional networks and extreme learning machines. This combination slashed the amount of time required for testing and outperformed deep non-recurrent networks. A YOLOv4 and Kalman filter-based object recognition and tracking system was proposed by Gao[19], *et al.* to improve the regulatory capability of sand mining and to make the most use of video resources obtained by video surveillance systems.

The N-YOLO-Tracker with YOLO V3 and a correlation-based tracker were used to develop a real-time object detector and tracker by Jha[20], *et al.* Ahmed[21], *et al.* introduced a real-time person-tracking solution for smart video surveillance based on the Siam Mask network. Sun[22], *et al.* demonstrated a novel approach to visual tracking based on CNN-ELM. The combined CNN-ELM tracker is resistant to changes in object characteristics like lighting, occlusion, and rotation in a video clip. Zhang[23], *et al.* presented a weighted online extreme learning machine-based robust tracking approach whose performance against challenges like occlusion, illumination, etc. was very effective.

So, as a result of reading articles on ELM and DL algorithms, it has been concluded that the selection of algorithms should be based on the requirements of the application. ELM is the greatest choice if an application is looking to shorten the time it takes to train a model, whereas DL is the better choice if it is looking to shorten the time it takes to test a model. This is because ELM can take a little longer to test in certain circumstances, and the dataset needs to be large enough. Also, the combination of ELM and DL yields strong results, which make use of the benefits offered by both technologies and compensate for the shortcomings of the other. This combination has significance for the effectiveness and safety of military missions.

2. METHODOLOGY

In the suggested approach, the feature learning process is done by using DWT (Discrete Wavelet Transform), and an ELM (Extreme Learning Machine) technique is used to classify data. The detailed block diagram of the suggested technique has been given below (Fig. 1).

Once the first frame's position of the target item has been defined, the suggested approach will locate the object in subsequent sequenced frames. This method used the object-tracking technique which is described in subsequent steps:

Step 1: Use the.jpg (.jpeg) format to record video. Otherwise, convert the video file into the required format.
Step 2: Obtain the information from the.jpg file by reading it.
Step 3: The first frame from the video should be read about the frame number.
Step 4: Convert the image that was provided as input into an

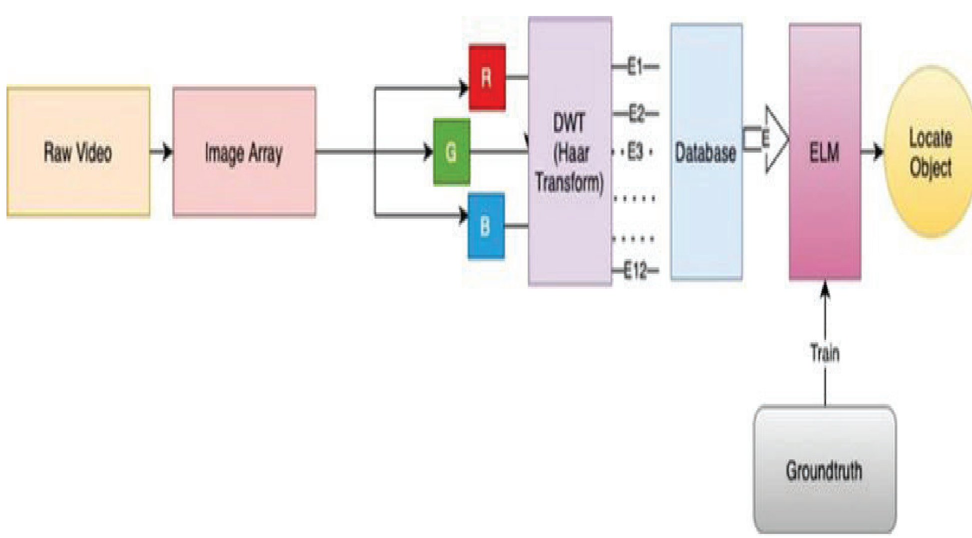


Figure 1. Schematic of the suggested method.

array.

Step 5: Find out the RGB component of the image array.

Step 6: Apply DWT (Haar Wavelet Transform) on each R, G, and B component of the image array and find out the set of energies.

Step 7: Store these energies in the database.

Step 8: Train ELM by applying both the ground truth of the image and energy E (a combination of a set of energies) as an input.

Step 9: Finally, we get the location of the target object in each subsequent frame in the input video.

The suggested framework is broken down into two phases: training and testing. The ELM network is trained using a collection of labeled training samples in the training phase. The training samples consist of a target object's image and its corresponding ground truth bounding box coordinates. Through training, the ELM network uses a single hidden layer of randomly generated neurons to establish a mapping between the input image and the output bounding box coordinates. Analytical computation of the output layer weights is achieved by taking the Moore-Penrose pseudo-inverse of the outputs of the hidden layer.

In the evaluation phase, the suggested system takes a video sequence as input and estimates the position of an object in each frame to carry out object tracking. In the first frame, the system uses the user-defined bounding box to set the initial position of the target item. The ELM network then takes the current frame's image as input and predicts the target object's position using the learned mapping. The system updates the bounding box coordinates based on the predicted position and repeats this process for each subsequent frame.

The components used in the proposed method are discussed in the subsequent section:

2.1 Feature Extraction

This process consists of extracting important features from video (which consists of several frames) to accomplish reliable classification. In defence and military operations, feature extraction is critical. It allows for the processing and analysis of data from diverse sources, resulting in better situational awareness, threat identification, decision-making, and military mission accomplishment while minimizing risks. In the proposed method, we use DWT (Discrete Wavelet Transform) to carry out the feature extraction process. DWT is an effective and practical tool for signal and image processing applications and it will be included in a great deal of newly developing standards. When converting a signal to an image, DWT employs both low-pass and high-pass filters. The outputs of these filters are divided by two to create a down-sampled signal. The number of bits included in the down-sampled outputs is the same as that of the signal being entered. The original signal may be recovered in its entirety by combining the up-sampled results of the low pass filter with the high pass filter. The process is repeated by feeding the results of the high pass filter into a second set of filters[24-28]. Haar wavelet transform is the most straightforward example of discrete wavelet transformation. In the suggested study, we employ the Haar wavelet transform since it offers the best performance in terms of computation time, very fast computation, little complexity, and clear results and it saves on storage space because it does not require a temporary array for calculation[29]. Haar transforms are employed for image processing and pattern identification due to their minimal computational needs.

A mathematical expression for haar wavelet transform is given as:

$$\Psi^{j}{}_{i}(x) := \Psi\left(2^{j} x - i\right) \qquad i = 0,1,2,\ldots,2^{j-1}$$

where,

$$\Psi(x) := \begin{cases} 1, & 0 \le x < 1/2 \\ -1, & 1/2 \le x < 1 \\ 0, & otherwise \end{cases} \tag{1}$$

2.2 Network Training

Extreme Learning Machine (ELM) is used for both training and classification in the proposed model. The ELM method is predicated on a theory of learning for Single-Hidden-Layer Feed-Forward Neural Networks (SLFNs), where the hidden layer need not consist of the same neurons as the rest of the network. For feed-forward NNs, gradient-descent-based techniques have traditionally been utilized. Tuning all of the parameters in these procedures is time-consuming. In contrast, an ELM has just one hidden layer and has completely arbitrary values for its parameters, weights, and biases. Using inverse operations, one may determine the weights of the output layer's connection to the hidden layer[30-31].

Where $X_i = \left[x_{i1}, x_{i2}, \ldots, x_{iN}\right]^T$ and $t_i = \left[t_{i1}, t_{i2}, \ldots, t_{im}\right]^T$ in the output function of a single hidden layer neural network which consists of N random distinct samples (X_i, t_i) and L hidden layer nodes, can also be written as:

$$f_L(x) = \sum_{j=1}^{L} \beta_j \, g(a_j, b_j, x_i) = t_i, i = 1,2,..,N \tag{2}$$

where, g(x) represents the activation function and $\beta_j = [\beta_{j1,}\beta_{j2,}\ldots\ldots\beta_{jm}]^T$ denotes the weight between the j^{th} hidden neuron and the output neuron. The above formula may also be expressed in a more condensed manner as:

$$H\beta = T \tag{3}$$

where

$$H = \begin{bmatrix} g(a_1, b_1, x_1) \ldots\ldots\ldots g(a_L, b_L, x_1) \\ :::::::::::::::::::::::::::::::::::::: \\ g(a_1, b_{1,} x_N) \ldots\ldots\ldots g(a_L, b_L, x_{L)} \end{bmatrix} \tag{4}$$

$$\beta = \left[\beta_{1,} \ldots\ldots\ldots \beta_L\right]^T = \begin{bmatrix} \beta_{11} \ldots\ldots\ldots\ldots \beta_{1m} \\ :::::::::::::::: \\ \beta_{L1} \ldots\ldots\ldots\ldots \beta_{Lm} \end{bmatrix} \tag{5}$$

$$\mathrm{T} = \left[T_{1,} \ldots\ldots\ldots T_N\right]^T = \begin{bmatrix} T_{11} \ldots\ldots\ldots\ldots T_{1m} \\ :::::::::::::::: \\ T_{N1} \ldots\ldots\ldots\ldots T_{Nm} \end{bmatrix} \tag{6}$$

In this Eqn., H stands for the output matrix of the neural network's hidden layer, T for the matrix of the output layer, and β for the output weight matrix. The formula for calculating the output weights in ELM is as follows: β=*HT*. In this case, the Moore-Penrose generalized inverse of the matrix *H* is denoted by the symbol $H\dagger$.

The frames from the video being tracked serve as input *X*, while the bounding box coordinates of the object being tracked serve as output *Y* in each frame. The ELM model is trained to use the hidden layer representation to create a mapping between the input frames and the output bounding box coordinates.

3. EXPERIMENT AND EVALUATION

A MATLAB 2022b software is used to implement the proposed tracker with MacBook Air, Apple M2 chip, 16 G RAM, Macintosh HD (256 G) startup disk, and Ventura 13.1 Mac OS system. In the suggested method MATLAB image processing, computer vision, and wavelet toolboxes to implement the algorithm have been employed. In the course of our research, an analysis has been conducted on a portion of the video sequences that are included in the Online Object Tracking (OTB 2013) benchmark dataset, which are divided into two groups, one for training and one for testing, with a one-to-one ratio (1:1). That is, the first half of the video frames are used to train ELM, together with any accessible ground truth. The testing set consists of the remaining images and is used to measure the accuracy, precision, and Center Location Error (CLE) graph to determine how well the proposed model performs.

The Online Object Tracking Benchmark, often known as OTB, is a visual tracking benchmark that is frequently utilized to test the effectiveness of a visual tracking system. The dataset known as OTB 2013 is comprised of a total of 51 video sequences, each of which is hampered frame-by-frame by bounding boxes and challenge characteristics. The proposed model performed single object tracking and tested on video sequences named- basketball, crowds, car dark, bolt, singer 2, etc. with associated challenges like- Illumination Variation (IV), Occlusion (OCC), Deformation (DEF), Out-Of-Plane Rotation (OPR), Background Clutters (BC) and In-Plane Rotation (IPR).

Visual results on the basketball video frame sequences of the OTB dataset are shown in Fig. 2. These figures with frame numbers illustrate how the proposed tracker accurately tracks the object in the presence of various challenges like occlusion, deformation, etc.

Table 1 provides a comparison of the proposed and several current trackers concerning accuracy and precision characteristics. The other values of both the parameters for the OTB-2013 dataset have been taken from[41-61]. The implementation code of ELM is taken from[43]. This table shows that both the parameters (accuracy and precision) are greater than the existing trackers, so the proposed one is better than the mentioned trackers.

The center location error is one of the figures of merit that are used in the evaluation of object tracking algorithms. This figure expresses the Euclidean distance that exists between the center of the tracked object's bounding box and the center of the ground truth bounding box. True object locations in a video sequence are represented by the ground truth bounding box, which is the manually annotated bounding box for each frame. The center location of objects is depicted in Figure 3.

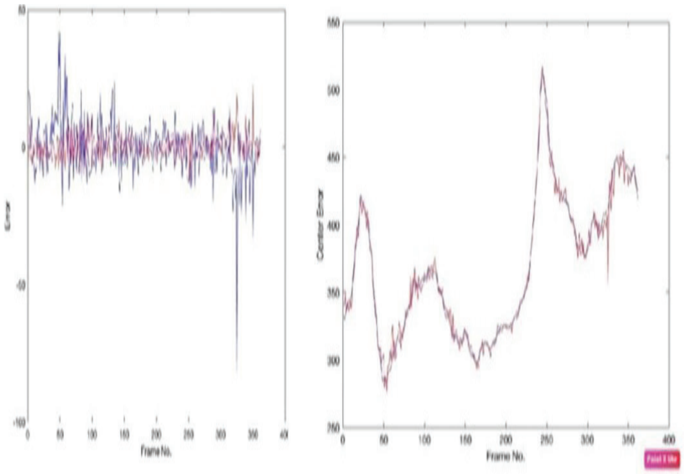
Table 1. Comparison of various trackers based on accuracy and precision attributes

TRACKERS	OTB-2013	
	Accuracy	Precision
SINT [32]	0.64	0.85
SIAMFC[33]	0.61	0.81
DSiam[34]	0.64	0.81
StructSiam[35]	0.64	0.88
TriSiam[36]	0.62	0.82
SiamFC+[37]	0.67	0.88
SE-SiamFC[38]	0.68	0.90
PrDiMP-50[39]	0.75	0.70
SiamFC++[40]	0.75	0.70
STMTrack[41]	0.80	0.76
Proposed	0.84	0.98

Figure 2. Tracking result of proposed tracking algorithm (mentioned frame number-1, 101, 355 (first row from left to right), 655, 705, 724 (second row from left to right)).

It is clear from Figure 3(a), that the ELM-based approach has tracked the object as per the ground truth. However, there is a small error in between. The center location error is used to assess how accurately the tracker can maintain the object's position over time. Figure 3(b) shows the center location error for the proposed method. In Figure 3(b), the center location error is within the limit of +/- 25 pixels except for a few frames having very high illumination because similar images are also not present in the training dataset.

In object tracking, the goal is to keep the center location error as small as possible, indicating that the tracker is accurately following the object's movement. The tracker can precisely retain the item's position in each frame with just a



Figur 3. Analytic of the proposed model through graphs. (a) Testing analysis (b) CLE analysis.

small center location error, even if the object is rapidly moving or changing in appearance or scale.

4. CONCLUSION AND FUTURE SCOPE

In this study, we suggested an ELM-based object tracking system that estimates the location of the target object in a sequence of videos by employing a single-hidden layer feed forward neural network. Object tracking in video sequences is a task that the ELM algorithm's random feature mapping technique performs since it is computationally economical and less likely to result in overfitting than other approaches. In terms of accuracy and precision, the suggested system achieves better results than state-of-the-art object tracking algorithms when tested on benchmark datasets from OTB-2013. The results of the experiments proved that the developed system is both useful and has the potential to be applied in real-world applications. Single object tracking enables precise identification and monitoring of specified targets, resulting in more effective and efficient actions while minimizing the potential of collateral damage. It is critical in many elements of military and security operations, from intelligence gathering to precision targeting and special operations.

The ELM-based object tracking has significant potential for future research and development. As the field continues to grow, it is expected to have more accurate, efficient, and robust object-tracking solutions that can be applied in various real-world scenarios where challenges lie in object tracking, especially in complex scenarios such as occlusion or fast motion. ELM-based techniques can be extended to handle multiple objects simultaneously. The defence and military industries might witness substantial future growth in the following sectors with single object tracking: Increased Precision and Accuracy, C4ISR (Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance), Multi-Sensor Fusion, Counter-Drone Operations, Cognitive Computing, Satellite-Based Tracking, Quantum Sensing, etc. We can also use some mathematical parameters other than accuracy, CLE, and precision to elaborate or find the success of our methodology such as Intersection Over Union (IoU), F1 score, RMSE, the Area Under The Curve (AUC), success rate, frame per second, processing time, failure rate, etc. The proposed object tracking is affected by environmental changes such as changes in lighting and camera movements. ELM-based techniques can be made more robust to these changes to ensure accurate tracking in different scenarios.

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