International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I6P229

Volume 70 Issue 6, 279-286, June 2022

Original Article

Object Tracking using Multi Adaptive Feature Extraction Technique

Sreehari Patibandla[1], Maruthavanan Archana[2], Rama Chaithanya Tanguturi[3]

[1]*Department of Computer Science & Engineering, Annamalai University, Tamil Nadu, India.*
[2] *Department of Information Technology, Annamalai University, Tamil Nadu, India.*
[3]*Department of Computer Science & Engineering, PACE Institute of Technology and Sciences, Andhra Pradesh, India.*

[1]sreehari.44@gmail.com

Received: 22 April 2022 Revised: 30 May 2022 Accepted: 02 June 2022 Published: 29 June 2022

Abstract *- Object tracking is a complex issue in computer vision; despite fast motion and motion blur, most relevant techniques have produced lesser performances. To overcome the complex issues of feature extraction, the enhanced technology of the Multi Adaptive Feature Extraction (MAFE) technique is proposed in this paper that has identified the sub-template feature for the object tracking process. The similarity values of the sub-template feature have been computed through the histogram, and they can be identified with the similarity matrix function. The classification process is enabled with Jeffrey's entropy that the updated sub-template. The performance evaluation involves the VTB dataset for evaluating the performance of the proposed MAFE technique, which is compared with the related techniques. The result proves that the proposed methodology has an improved success rate than other techniques.*

Keywords *- Object tracking, Multi Adaptive Feature Extraction, Jeffrey's entropy, success rate, the posterior probability.*

1. Introduction

Object tracking is the most useful technique in the computer vision domain with the development of artificial intelligence methodology. Many applications like intelligent interaction with humans and video surveillance [1]. The conventional tracking techniques have been limited to the generative tracking task, with the help of the appearance data of the particular object; the generative trackers generate the specific model and find the similarity of every frame through the smallest amount of reconstruction fault [2]. A monitoring methodology finds a subspace model that monitors the modifications of the objects that involve the problems of scale variance and occlusion. A real-time object tracking technique has been implemented through the optimization approach, which identifies the shape of every frame and demonstrates the uncertainty in the evaluation process [3]. The reboot-based tracking technique has been implemented the feature identification into the object tracking that the self-adaptability is the main issue.

Several correlation filters have been identified to improve the object tracking to provide good results. The multi-task correlation technique strengthens the fitness task [4]. The common occlusion of the complex objects through the target-based object tracking process. The enhanced multi-object tracking technique has been implemented through the segmentation-based tracking system with advanced devices [5]. The discriminative filters are used to compute the filter through the regularization technique by calculating the resources. The supervised learning technique for visual representation is involved transfer learning through the threshold values on edge components [6].

This paper proposes the Multi Adaptive Feature Extraction (MAFE) technique, which identifies the appropriate tracking feature with the iteration technique. The similarity of every feature of the sub-template has been measured through the separable concept of dissimilar features of every object by the posterior probability functionality. Jeffrey's entropy is the most important parameter for implementing the feature extraction, generating the target template, and minimizing the conflicts of the template. The texture and color features are involved in maximizing the effectiveness of the proposed technique and applying several video sequences from the VTB dataset. The proposed technique has been constructed to improve success and diminish location errors in complex environments.

The main contribution of the paper is

- ✓ The sub-template of every feature is characterized and computes the similarity matrix with the posterior probability function.
- ✓ The computation of Jeffrey's entropy is used as the important parameter for analyzing the similarity value.
- ✓ The measurement of dissimilarity within the categories has been identified more accurately.
- ✓ The Multi Adaptive Feature Extraction (MAFE) technique is proposed to enhance object tracking performance.

2. Related Works

The object tracking process is emerging research as several researchers have been spotlighting the improvement of accuracy from several aspects like classifier design and feature extraction. Using the improvement of several techniques, specific development has been accomplished [7]. The target-based object tracking is an improved technology that provides the accuracy of several occlusions [8]. The automatic tracking technique has been developed to obtain the targets through the confidence score function as deflect bounding boxes are identified for enhancing the accuracy of the object tracking process [9]. The target location has been estimated through the combined prediction technique, which exploits the current frames with adjacent frames through the Hungarian technique [10]. The occlusions have been handled through the data-based motion technique that the adjacent frames could not be correlated with the present frame target whenever the occlusion happens [11].

The real-time object tracking technique has been implemented by estimating the location of the identified targets. The Kalman filter is combined with the temporal data to avoid location errors [12]. The Kalman filter value is updated whenever the target is identified in the video sequence within the specified time. The confidence score of the final tracking is involved in generating the final prediction assessment [13]. The generated data is associated with the specific scores related to the suppression technique. The unassigned tracks are identified through the predetermined threshold value, and the others are discarded for obtaining the effective object tracking [14]. The object tracking technique of YOLOv2 [15] has been trained on human-based frames that the back projection of 3-dimension space to generate the enhanced model. The refinement technique with the clustering concept has been constructed with the features of a histogram-related appearance framework to evade the difference within the target values.

The online tracking technique has been implemented with the batch processing technique, enabling the re-identification process once the occlusion is completed. The methodologies like SORT [16] and MOT15 [17] have produced high inferences with the affinity function in 3-dimension space. The object tracking process has the confidence score to track the objects in good quality as the tracks are connected with the target values. The learning-based appearance technique has been implemented as ILDA [18] with a deep learning framework to process the image-related tracking system using context parameters.

3. Proposed work

The feature extraction involves the dissimilar image feature for computing the similarity within the matched area and the targeted area as the parameter for identifying the specific tracking process. The enhanced technique has been framed to utilize the adaptability of dissimilar features in various scenarios. Whenever the condition changes, find the common feature for tracking the target as that technology has the extensibility for combining several features in a methodology for object tracking. The proposed framework has been adapted to the template matching technique. The measurement of every feature to segregate the background for finding the specific feature for tracking the adjacent frame is illustrated in Figure. 1.

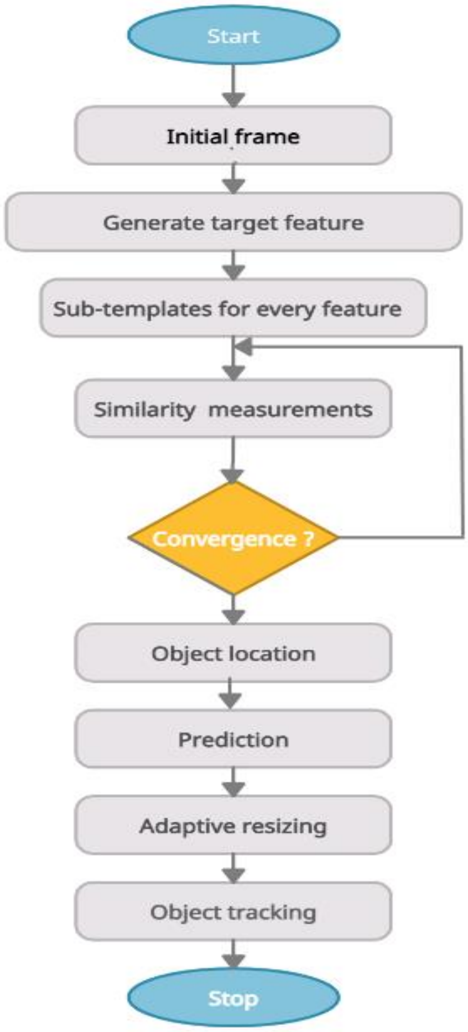

Fig. 1 Proposed framework for object tracking

The proposed framework consists of the entire details of object features that the computation of every feature into the targeted area with the similarity matching. The target feature description in the initial frame into the matching area in every adjacent frame. The computed optimal feature in the adjacent frame is identified as the specific feature in completing the tracking process. Additionally, the object's location is computed regularly due to the similarity probability condition. The multi-feature has been selected to the common location of the object and segregates the background of the identifying area by computing every frame's similarity.

The proposed algorithm computes the operator value of every feature, generates the sub-template of every target feature, and joins every feature to demonstrate the targeted area. The accuracy for object tracking is achieved by minimizing the dimension of the feature vector and identifying the exact feature values. The features of every sub-template have been demonstrated through the feature-based histogram values that the highest posterior probability is used for computing the similarity measurement in Eq. (1).

$$\gamma_{b_j}^{i} = \sum_{a_j \in P_{b_j}} s^{i}(a_j) \qquad (1)$$

Where $\gamma_{b_j}^{i}$ is the similarity function, $s^{i}(a_j)$ is the matched value for the sub-template. The similarity value for the sub-template is computed in Eq. (2).

$$s^{i}(a_j) = \frac{t_u^{i}(a_j)}{f_u^{i}(a_j)} \qquad (2)$$

Where t_u^{i} is the template for the targeted area, f_u^{i} is the template for finding the area. According to the sub-templates, the targeted area has been demonstrated by every feature that must be matched with the finding area. The feature map is related to the similarity value of every sub-template. The posterior probability, along with the similarity index, has been computed by every sub-template with several similarity value matrices implemented through dissimilar sub-templates. The construction and measuring of the dissimilarity within the edge point of the finding area of every sub-template similarity matrix through every adjacent frame.

Collecting the prior data is a complex task that the data is always uncertain as to the real-time issues. Hence, the improved tracking technique is more accurate for the long-term task. This issue can be eliminated by segregating every frame for the targeted view. The classifier is used to demonstrate the tracking task through the classification for obtaining the object; this segregation process has been demonstrated with the object tracking procedure. Additionally, the tracking features of the particular frame by computing the feature extraction process of the objects with the frames.

The sampling process of the tracked objects has been developed using the mathematical formation for computing the distance within the two adjacent classes while the dissimilar features should be measured. The sampling procedure could find the regions with a similar task size through the optimization technique for the targeted area to maintain an accurate classification. The sub-template process will eliminate the computational complexity to measure the specific feature more accurately. The posterior probability is computed to identify the similarity within the targeted area.

Fig. 2 demonstrates the selection procedure for sub-template that the similarity within the positive values and the target value, which is denoted as $\gamma_m^{i,po}$ the similarity between the negative values and the target value is denoted as $\gamma_n^{i,ne}$. The sub-template selection process is segregated into positive similarity values and the negative similarity values,

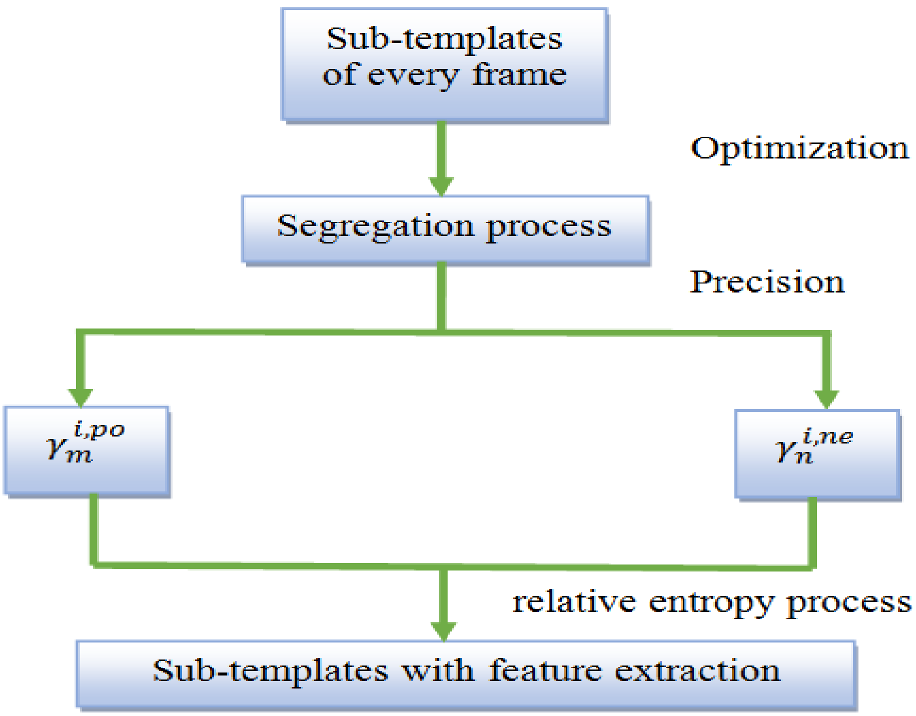

Fig. 2 The selection procedure for sub-templates

The related entropy is computed using the asymmetric values within the probability distribution of α and β. It is the parameter of the total amount of bits needed to complete the encoding procedure. The relative entropy value is zero whenever the 2 functionalities are similar values. The feature vectors $\alpha = \{\alpha_i\}_{i=1}^{n}$ and $\beta = \{\beta_i\}_{i=1}^{n}$The condition for the feature vectors is computed in Eq. (3).

$$\sum_{i=1}^{n} \alpha_i = \sum_{i=1}^{n} \beta_i = 1 \qquad (3)$$

The relative entropy $RE(\alpha, \beta)$ is computed in Eq. (4).

$$RE(\alpha, \beta) = \sum_{i=1}^{n} \alpha_i \log \frac{\alpha_i}{\beta_i} \qquad (4)$$

Jeffrey's entropy is used to transform the asymmetric values into the symmetric values in Eq. (5)

$$JE(\alpha, \beta) = RE(\alpha, \beta) + RE(\beta, \alpha) \qquad (5)$$

The convergence value is computed in Eq. (6).

$$\delta(\alpha, \beta) = ||\alpha - \beta||^2 = \sum_{i=1}^{n} (\alpha_i - \beta_i)^2 \qquad (6)$$

The value of α_i, β_i is computed in Eq. (7) and Eq. (8), respectively.

$$\alpha_i = \frac{1}{c_1} \sum_{k=1}^{c_1} \left(f_k^{(1)}\right)^2 \qquad (7)$$

$$\beta_i = \frac{1}{c_2} \sum_{k=1}^{c_2} \left(f_k^{(2)}\right)^2 \qquad (8)$$

Where c_1 is the total amount of samples of $class_1$ and c_2 is the total amount of samples of $class_2$, $f_k^{(1)}$ denotes the frame details of $class_1$ and $f_k^{(2)}$ denotes the frame details of $class_2$. The separate parameter of every feature is computed in Eq. (9).

$$SP^i = \sum_{i=1}^{k} (\bar{\gamma}^{i,po} - \bar{\gamma}^{i,ne})^2 \qquad (9)$$

The mean squared positive similarity is computed in Eq. (10)

$$\bar{\gamma}^{i,po} = \frac{1}{X} \sum_{k=1}^{X} \left(\gamma_k^{i,po}\right)^2 \qquad (10)$$

The mean squared positive similarity is computed in Eq. (10)

$$\bar{\gamma}^{i,ne} = \frac{1}{Y} \sum_{k=1}^{X} \left(\gamma_k^{i,ne}\right)^2 \qquad (11)$$

The object tracking procedure has the template that the object for updating the targeted area according to the highest posterior probability similarity criteria. The high dimensional multi-feature template has to minimize the template conflicts as the sub-template concept is constructed according to every frame that the adaptability of completing the modifications of the object tracking procedure whenever demonstrating the sub-template enhancement feature for updating to be adopted.

Algorithm - Multi Adaptive Feature Extraction

Step 1: Fix the target location of the last frame as the beginning location and compute the colour feature-based texture for finding the area in the beginning location.

Step 2: Compute the similarity values of every pixel in the finding area into the present frame for positioning the tacking process.

Step 3: Initialize the iteration value of k=0.

Step 4: Compute the location of the matched value for the remaining iterations using Eq. (12).

$$b_{i+1} = \frac{\sum_{a_i \in A_{b_i}} a_i \, s(a_i)}{\sum_{a_i \in A_{b_i}} s(a_i)} \qquad (12)$$

Step 5: Process step 4 until $||b_{i+1}|| < \varepsilon$

Step 6: Compute the texture features in the present frame using Eq. (12).

Step 7: Compute the target size modification using Eq. (13).

$$\rho(i+1) = \begin{cases} \rho(i+2) + 2, & if\ \bar{\vartheta}_{-1} > 0.80\ and\ \bar{\vartheta}_1 > 0.60 \\ \rho(i-2) - 2, & if\ \bar{\vartheta}_0 < 0.60\ and\ \bar{\vartheta}_1 < 0.30 \\ \rho(i), & Otherwise \end{cases} \qquad (13)$$

Where i is the total frames of the image, $\rho(i)$ is the target template size, $\bar{\vartheta}_i$ is the mean posterior probability.

Step 8: The updated target value is computed in Eq. (14).

$$\bar{\vartheta}(\alpha, \beta) \geq \emptyset \qquad (14)$$

Where $\emptyset$ is the threshold value.

Step 9: The target sub-template feature value is computed using Eq. (15).

$$\beta' = \omega\alpha + (1-\omega)\beta \qquad (15)$$

Where ω is the weighted value, β' denotes the feature vector for the target template value.

Step 10: Process the remaining images from step 1 to step 9.

4. Performance Evaluation

VTB dataset [19] has been used for performing the evaluation that the proposed technique is compared with the relevant techniques of KCF [20], DSST [21], and LBPT [22]. The dataset has the video sequences with different representations of Walking, Basketball, CarScale, MotorRolling, Shaking, Crossing, Dog, and Soccer for completing the object tracking process. Fig. 3 demonstrates the video sequences used for completing the performance evaluation.

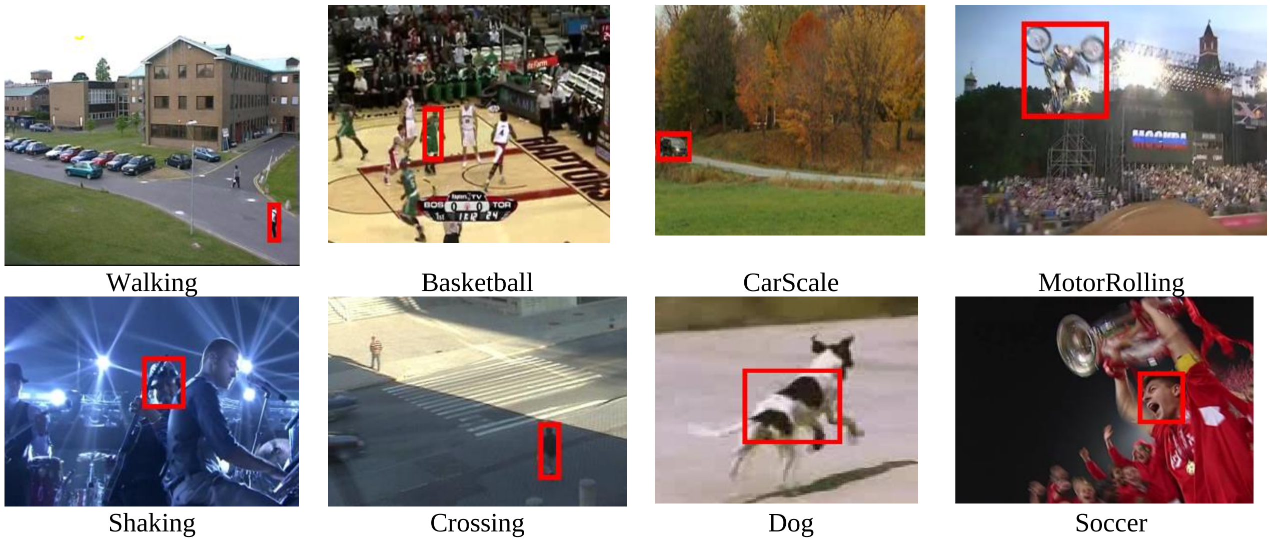

Fig. 3 Video sequences used for experiments

The efficiency of the proposed technique is identified using the location error concept that computes the Euclidean distance of the tracking area, and it is computed using Eq. (16).

$$LE = \sqrt{(a_1 - a_2)^2 + (b_1 - b_2)^2} \qquad (16)$$

Where (a_1, b_1) demonstrates the location of the ground truth in a particular frame, (a_2, b_1) Demonstrates the center location of the tracking particular frame. Fig. 4 demonstrates the location errors of the proposed technique, which is compared with the relevant techniques that the proposed technique has the minimized location errors. The experimental results proved that the proposed technique enhanced object tracking whenever changing the objects or video sequences. The procedure for generating the target template will affect the object tracking if the template conflicts exist.

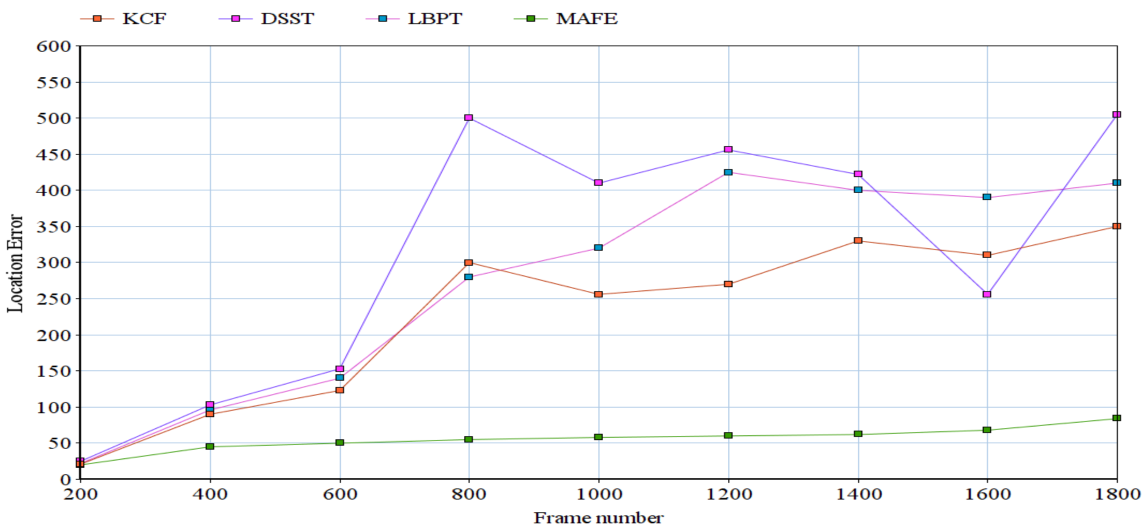

Fig. 4 Location error comparison

The success rate contains the object tracking using the Intersection over Union parameter, and it computes the ratio within the candidate area (Can_{area}) and the ground truth area ($Ground_{area}$) is which is demonstrated in Eq. (17).

$$IoU = \frac{Can_{area} \cap Ground_{area}}{Can_{area} \cup Ground_{area}} \quad (17)$$

The success rate is computed in Eq. (18).

$$SR = \frac{Tracked_{Frame}}{Total_{Frame}} \quad (18)$$

Where $Tracked_{Frame}$ is the total tracked frame and $Total_{Frame}$ is the total amount of frames for the specific video sequence.

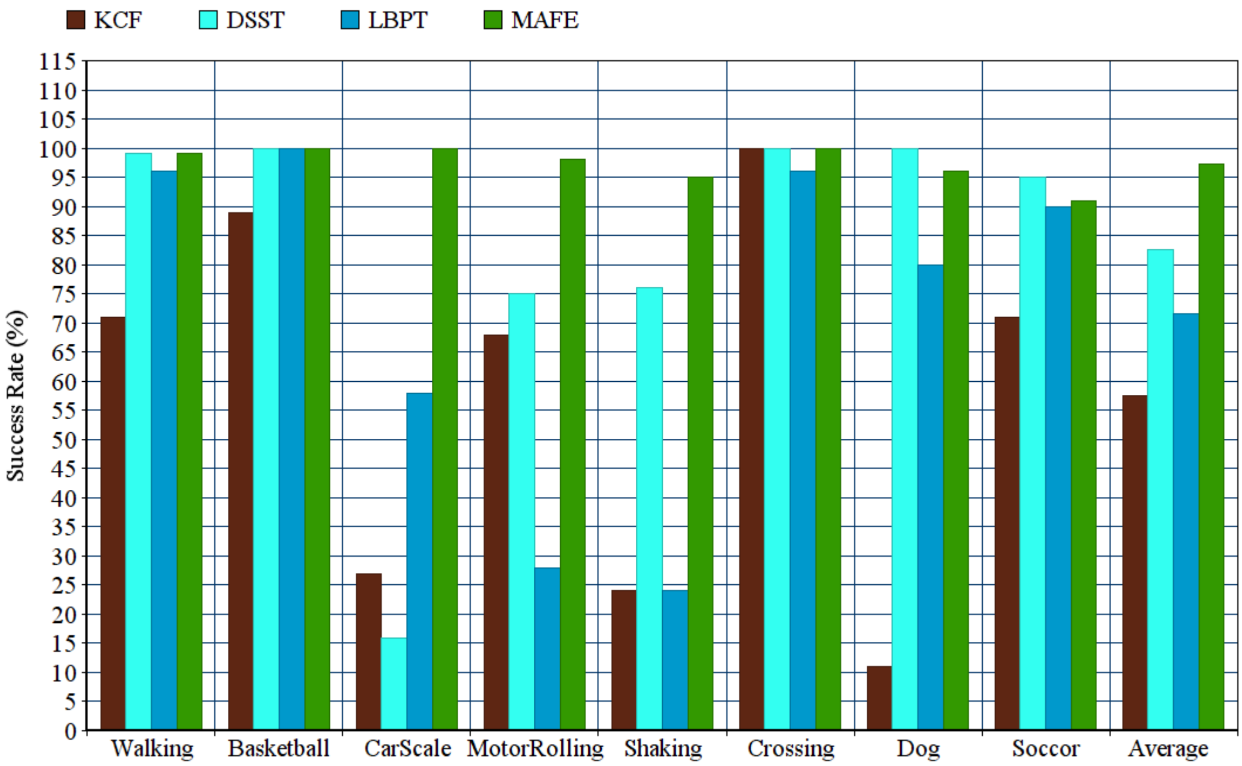

Fig. 5 Success rate (%)

The success rate is demonstrated as the successful object tracking process. The tracking process has been completed well through the tracking boxes that couldn't improve the target scale value. The colour sub-template with the combined feature can be connected with others to position the target values. The experimental results show that the single feature couldn't track the target enough, and some methods don't complete the target according to the occlusion or some object interferences. The proposed technique is very accurate for object tracking in the entire procedure. The result has been demonstrated in Fig. 5, as the proposed technique has an improved success rate compared with the related methods.

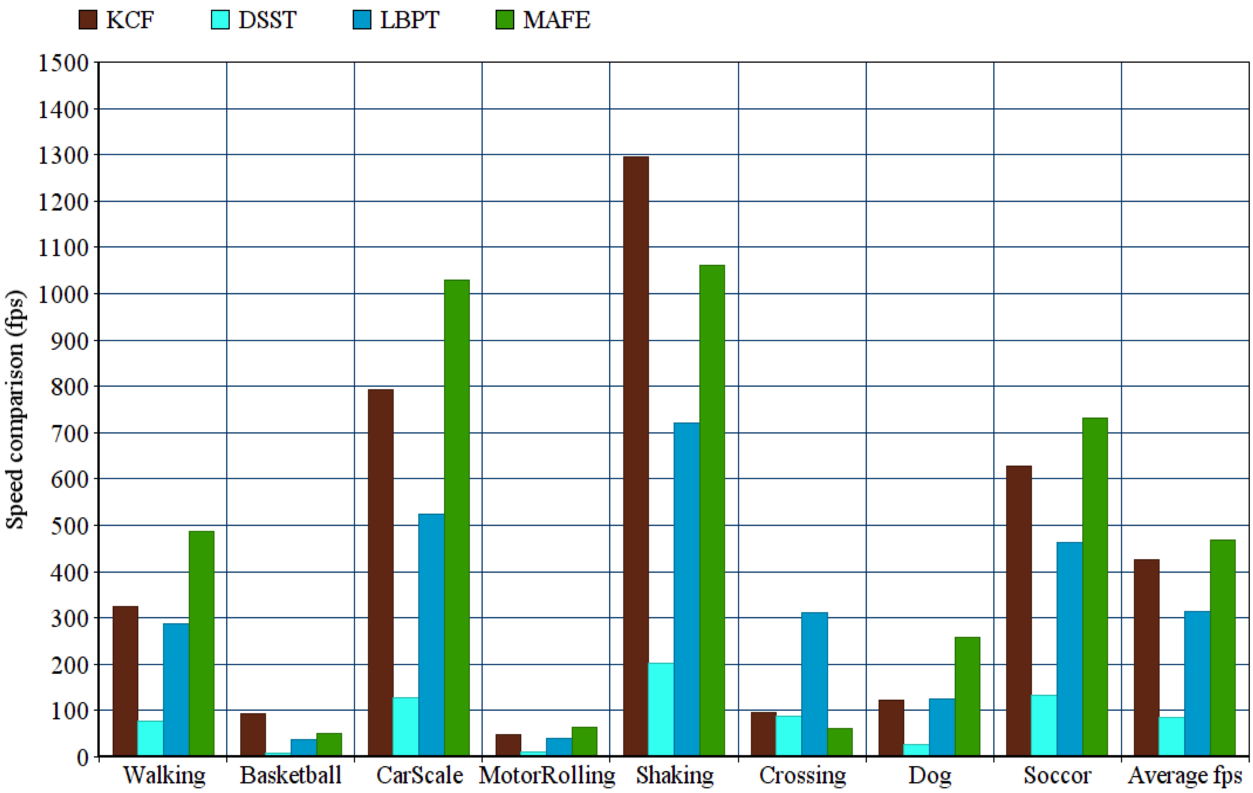

Fig. 6 Speed comparison

Fig. 6 demonstrates the object tracking of frames per second through the experiments that the proposed technique has a high amount of speed that the time-consuming process of the features and the sub-templates selections. Hence, minimizing the computation of positive and negative values and summarizing the finding area for enhancing the object tracking speed. Additionally, the speed of the object tracking is related to the multiple features and the feature vector dimensions.

The proposed technique includes multi-features for implementing the object tracking, like the edges and gradients included for generating the accuracy. The global feature-based histogram is utilized to get the colour information that the RGB feature has a feature vector with 512 dimensions. The sub-template is another feature in the global frame that the feature operator uses to get the object-related data's shape. The proposed technique has extensively identified the features within the texture and the colour.

5. Conclusion

The proposed Multi Adaptive Feature Extraction technique can solve the common issues of feature extraction in computer vision. The robustness of the proposed technique is achieved through finding the capable feature as it improves the inference speed for accuracy in edge applications. The performance of the proposed technique is evaluated through the VTB dataset, which has video sequences. The results prove that the proposed technique has obtained a maximum success rate, eliminates location errors, and outperforms the relevant techniques. Future work should be evaluated and decreasing the computational complexity and better accuracy.

Conflicts of Interest

Interest, professional growth, and inspiration by the head of the institution.

References

[1] Mangawati, A.; Leesan, M.; Aradhya, H.V.R. Object Tracking Algorithms for Video Surveillance Applications. In Proceedings of the International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 3–5 , (2018) 667–671.

[2] Verma, R. A Review of Object Detection and Tracking Methods. Int. J. Adv. Eng. Res. Dev, 4 (2017) 569–578.

[3] Riahi, D.; Bilodeau, G.A. Multiple Object Tracking Based on Sparse Generative Appearance Modeling, In Proceedings of the IEEE International Conference on Image Processing (ICIP), Quebec City, QC, Canada, 27–30 September , (2015) 4017–4021.

[4] Wu, Y.; Lim, J.; Yang, M.H. Online Object Tracking. A Benchmark. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Portland, OR, USA, 23–28 June, (2013) 2411–2418.

[5] Hare, S.; Golodetz, S.; Saffari, A.; Vineet, V.; Cheng, M.M.; Hicks, S.L.; Torr, P.H. Struck: Structured Output Tracking With Kernels. In Proceedings of the IEEE International Conference on Computer Vision, Barcelona, Spain, 6–13 November, (2011) 263–270.

[6] Kalal, Z.; Matas, J.; Mikolajczyk, K. Pn Learning: Boot-Strapping Binary Classiers By Structural Constraints. in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, San Francisco, CA, USA, 13–18 June, (2010) 49–56.
[7] Bolme, D.S.; Beveridge, J.R.; Draper, B.A.; Lui, Y.M. Visual Object Tracking Using Adaptive Correlation Filters. in Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Francisco, CA, USA, 13–18 June, (2010) 2544–2550.
[8] Zhang, T.; Xu, C.; Yang, M.H. Multi-Task Correlation Particle Filter for Robust Object Tracking. in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July, (2017) 4335–4343.
[9] Perez-Cham, O.E.; Puente, C.; Soubervielle-Montalvo, C.; Olague, G.; Aguirre-Salado, C.A.; Nuñez-Varela, A.S. Parallelization of the Honeybee Search Algorithm for Object Tracking. Appl. Sci., 10 (2020) 2122.
[10] Geiger, A.; Lauer, M.; Wojek, C.; Stiller, C.; Urtasun, R. 3d Traffic Scene Understanding From Movable Platforms. IEEE Trans. Pattern Anal. Mach. Intell, 36 (2013) 1012–1025.
[11] Chang, S.; Li, W.; Zhang, Y.; Feng, Z. Online Siamese Network for Visual Object Tracking. Sensors, 19 (2019) 1858.
[12] Kuang Chiu, H.; Prioletti, A.; Li, J.; Bohg, J. Probabilistic 3D Multi-Object Tracking for Autonomous Driving,(2020). Arxiv , Arxiv:2001.05673.
[13] Yang, H.;Wen, J.; Wu, X.; He, L.; Mumtaz, S. An Efficient Edge Artificial Intelligence Multipedestrian Tracking Method with Rank Constraint. IEEE Trans. Ind. Inform, 15 (2019) 4178–4188.
[14] Weng, X.;Wang, Y.; Man, Y.; Kitani, K.M. Gnn3dmot: Graph Neural Network for 3d Multi-Object Tracking With 2d-3d Multi-Feature Learning. in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle,WA, USA, 14–19 June, (2020) 6499–6508.
[15] Redmon, J.; Farhadi, A. YOLO9000: Better, Faster, Stronger, (2016). Arxiv, Arxiv:1612.08242. Available Online: Http://Pjreddie.Com/Darknet/Yolov2/
[16] Weng, X.; Wang, J.; Held, D.; Kitani, K. AB3DMOT: A Baseline for 3D Multi-Object Tracking and New Evaluation Metrics, (2020). Arxiv, Arxiv:2008.08063.
[17] Leal-Taixé, L.; Milan, A.; Reid, I.; Roth, S.; Schindler, K. Motchallenge 2015: Towards A Benchmark for Multi-Target Tracking, (2015). Arxiv, Arxiv:1504.01942
[18] Bae, S.H.; Yoon, K.J. Robust Online Multi-Object Tracking Based on Tracklet Confidence and Online Discriminative Appearance Learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, 23–28 June, (2014) 1218–1225.
[19] Http://Cvlab.Hanyang.Ac.Kr/Tracker_Benchmark/Datasets.Html
[20] Henriques, J.F.; Caseiro, R.; Martins, P.; Batista, J. High-Speed Tracking With Kernelized Correlation Filters. IEEE Trans. Pattern Anal. Mach. Intell, 37 (2014) 583–596.
[21] Danelljan, M.; Häger, G.; Khan, F.; Felsberg, M. Accurate Scale Estimation for Robust Visual Tracking. in Proceedings of the British Machine Vision Conference, Nottingham, UK, 1–5 September, (2014).
[22] Ning, J.; Zhang, L.; Zhang, D.;Wu, C. Robust Object Tracking Using Joint Color-Texture Histogram. Int. J. Pattern Recognit. Artif. Intell, 23 (2009) 1245–1263.