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Development of Adaptive Tracking using Advance Filter and Selection Features Method

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ABSTRACT

Recently, Kalman filter (KF)-based algorithms of tracking had demonstrated to be effective, however, their efficiency is limited by fixed feature selections and the possibility of model drift. In the presented research, we offer a new adaptive feature selection-based tracking approach that maintains the KF's excellent discriminating power. Depending on scores of confidence regarding features in every one of frames, the suggested approach might select (automatically) either SIFT feature or the colour feature for the tracking. With a use of KF, a response map related to the SIFT features and color features are retrieved first. The color features that distinguish the luminance from the color are extracted using the Lab color space. Second, the average peak-to-correlation energy is used for the determination of the confidence region and the target's possible location. Finally, a total of 3 criteria have been utilized in order to choose the appropriate feature for present frame in order to execute adaptive tracking. On OTB benchmark datasets, the experimental findings show that the suggested tracker performs better in comparison with other state-of-art techniques.

Keywords: Feature Selection, Kalman Filters, Object Detection, Object Tracking.

1 INTRODUCTION

Visual object tracking may be defined as an active aspect related to computer vision, with various applications in robotics, automation, and surveillance [1-3]. When a target is located in one of the frames, it is frequently used to follow the object in a set of the frames. In different visual tracking applications, the target's location is only known in the first frame, hence an estimate of the target's likely locations in subsequent frames is required. A lot of the current algorithms presume that the target location does not change much with the time and decide target inside search window that has been centered on previous item location, motion model [2-7]. Yet, a few complex conditions, like scale variation, illumination variation, occlusion, and scale variations, might not be suited for such algorithms [3-5]. Various algorithms for visual object tracking use either discriminative or generative approaches for learning an appearance model of the target. Also, the generating model [4-6], like the model of sparse coding [7-8], changes the object tracking problem into a sparse approximation problem, like CT tracker [9-12]. The tracking technique has been prone to drifting of the target frame in the case when there is a high noise level. The discriminative approaches are used by the majority of tracking algorithms, and the major idea is training on-line updated classifier that offers target location in every one of the frames KF technology in this approach easily conducts the complicated convolutional process in frequency domain that increases target tracking timeliness, attracting a lot of research interest in the field [10-15]. Various algorithms have emerged recently that combine deep learning and KF. Many depth convolution features related to convolution neural networks are utilized in depth features, which carry more developed semantic information [16]. In addition, target location is obtained using a depth feature correlation filtering approach through the calculation of relevant responses of the confidence regarding the features of the convolutional layer of various depth levels [17]. Even though the feature of the convolution's depth has a high capability for identifying the target, the feature transformation in the "black box" is difficult to grasp, and it also has a large computation complexity, thus, resulting method cannot attain real-time performance [18-20]. As a result, studying the KF technique without applying the depth convolution characteristics remains important. In the case when the discriminating power of 1 feature extremely differs from discrimination power of another feature, utilizing the 2 features together might lead to low tracking accuracy. Also, a tracker of the correlation filter depending upon the adaptive feature selection utilizing confidence score of the map of the response has been offered as a solution to this problem. In this study, we utilize the Kalman filter to determine the confidence score of response map for every one of the features (color and SIFT features in Labs colour space) that could be adaptively utilized in order to pick features. In the case where an object has been deformed, for instance, SIFT feature is greatly impacted. For the tracking, the colour feature which is less influenced compared to SIFT features are going to be chosen. In an event that the object's color property is significantly disturbed, the SIFT feature is going to be chosen for the tracking. The distinction between that approach and other tracking techniques is that more appropriate features have been chosen based on real situations of every one of the frames that causes an increase in feature selections' flexibility in complicated scenes and may more correctly characterize a target. The algorithm has been evaluated using OTB benchmark data-set and 100 of the video sequences, and its efficiency has been compared to that of a number of popular algorithms.

The following is the study's structure: In Section 2, a few related works are discussed briefly. In Section 3, we provide the suggested technique, which depend on the SIFT feature's confidence score and the color feature in the Labs colour space. The findings of the experimentation are presented in Section4. Ultimately, in Section5, the conclusions are presented.

2 RELATED WORKS

2 1: KALMAN Filter

KF tracking can be defined as an efficient linear recursive filter algorithm which may be done in a computer. It might successfully handle problems relating to linear Gaussian filters KF is used in Multi-hierarchical Independent Correlation Filters for Visual Tracking (MFT) [21] to build a motion estimation module that predicts the tracking target's trajectory For robust tracking with an edge KF [22] suggests the Strong Tracking Marginalized Kalman Filter (STMKF). When examining the object in 3D space, applying an attenuation factor in the Marginalized Kalman Filter (MKF) lowers the effect of the prior filter on the present filter. Reference [23] examines the performance regarding extended KF for tracking multiple and single objects with the use of azimuth.The performance of the article filter and KF for 2D visual multi-object tracking in diverse situations is compared in reference [24]. An approach for tracking and detecting moving objects with the use of KF is described in reference [25]. This approach, which is intended for situations where the object is obscured, can just anticipate the target position in the present frame based on the state of the target in the previous frame.The precision of the KF-based tracker, on the other hand, is limited, and the process of KF, which requires updating every frame, is prone to accumulating errors [25] uses an approach which is comparable to ours. We substitute target detection results with CF tracking findings. Our KFR module will now anticipate the target position in the current frame based on the target's status information from the previous frame

2.2. The Colour Features in the Labs Colour Space

Because majority of the image capturing systems now use RGB color space for output and input, the conventional approach is converting the colour images to the RGB colour space and extracting the colour characteristics. However, luminance information is contained in all of the 3 channels of the colour space of the RGB, and there has been a strong link between them. As a result, employing these directly might not be possible to achieve the required impact, Lab color space, unlike almost all typical RGB color space, does not depend on pigments or light. The International Lighting Committee (CIE) established a color system that may theoretically depict all colors found in nature L denotes luminance in three-channel Lab colour space component, with a range of [0, 100] and the luminance increasing with the numeric value Both b and a channel have ranges of [128], [127]. The color properties of the Lab color space were employed for object tracking in our tests.

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3 PROPOSED APPROACH

The formulation of the problem of adaptive feature selections approach depending upon score of confidence is presented first in this section. After that, we devise a method for bridging the gap between the well-known KF and our problem description. The difficulty of determining whether the tracking result is precise is crucial since it dictates the model's updating strategy. Various algorithms, like SRDCF, DSST, and Staple, don't judge accuracy of the tracking findings, and each frame's results have been updated every n frame or instantly. Which is not reliable, particularly in the case where a target has been obscured or tracking is poor, and after that, updating the model that will just make a tracker increasingly incapable of identifying the target, a phenomenon known as model drift? In KF tracking, each frame's response map should ideally be a single peak, with the maximal response map value corresponding to the present frame's tracking results location. The tracking result is more credible if the single spike in a response map is sharper; conversely, tracking result has less credibility if single spike is flatter. The actual response map could be multi-peak since the actual scene is affected by complex factors, and right target position could be at maximum response map peak It could as well be at a different peak, such as a secondary peak. The average peak energy and maximal score of the response F_{max} of a response map are combined to appropriately evaluate the effectiveness F_{max} is defined as:

$$F_{max} = max\ (F_{w,h}\ (T\ (x_t\ ,\ p\ );\theta_{t-1}\ )) \qquad (1)$$

In general, highest point F_{max} value in a response map denotes central position result, however, if only this condition has been utilized for the selection of the features, model drift phenomenon occurs in the case wherethere is a number of the peaks in response map, F_{max} doesn't reflect the oscillation degree of a response map, a new criterion that has been referred to as the average peak energy ($APCE^t$) has been utilized, where:

$$APCE = (\ F_{max} - F_{min}\ )^2\ /\ mean(\textstyle\sum(\ F_{w.h} - F_{min}\ )^2) \qquad (2)$$

In the case of beginning a new tracking with the use of discriminative approaches, the aim is learning a proper classifier that might be extracting target from a background in the real time In 1st frame, a target location is known It is capable of directly getting color and SIFT features, with the use of kalman's filter In the present study, confidence score has been utilized for evaluating reliability every one of the features and adaptively selecting the proper feature throughout target tracking.

Assuming the fact that there is a total of t frames $X = [X_1, X_2, \ldots, X_t]$.

Given target location in X_1, a discriminative kalman's filter is learnt in SIFT features and score F_{SIFT} is gotten at every one of the pixels in a response map. After that, the RGB image color is converted into Lab color space Kalman filters are learnt as well in the color feature in order to compute score F_{-color} Due to the fact that the target location in 1st frame is known, (2) has been utilized for getting a standard score of confidence M_{-SIFT} and M_{-color} in 1st frame for measuring the following frame's reliability. Threshold has been set for the evaluation of the following frame's reliability that has been represented as:

$$Threshold_{SIFT} = 30\% * M_{SIFT} \qquad (3)$$

$$Threshold_{color} = 30\% * M_{color} \qquad (2)$$

In the case where the following frame's score is higher compared to threshold value, this frame has been considered as valid frame is considered invalid that will result in causing the drift of the model and has been disregarded. Benchmark queue performs the storing of the scores of 3 of the valid frames and obtains mean value of the score as a benchmark:

$$S_{base} = \sum_{t=1}^{n} APCE^t / n \qquad (4)$$

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In the present study, 3 indicators have been utilized for adaptively selecting optimum features. Initially the response map APEC score is a representation of degree of confidence of the current frame. The 2 score types have been put under same standard and then they have been compared. Due to the fact that M_{-SIFT} and M_{-color} represents standard score, a ratio is set for the transformation of $APCE_{-color}$ to $APCE_{-SIFT}$, which can be represented in the following form:

$$Ratio^t = (APCE^t_{color} * M_{SIFT} - M_{color} * APCE^t_{SIFT})/M_{color} \quad (5)$$

In the case where the value of ratio has been greater than 0, the feature of the color is more sufficient compared to SIFT features. Secondly, a rate of score changing has been set for measuring the degree of the confidence, which can be represented as:

$$Change\_ratio^t = APCE^t - S_{base} / S_{base} \quad (6)$$

In the case where SIFT feature rate is higher than color features, stable color feature is selected in such case or else, the other one is chosen. Ultimately, position off-set of maximal response map value F_{-max} *is* calculated in this frame from previous one, which can be represented as:

$$\Delta^t = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2} \quad (7)$$

Due to the fact that normal tracking smoothly changes between the neighboring frames, in the case where there are sudden changes in maximal value offset, the drift of the model has been considered to occur. Smaller distance of every one of the features is chosen through performing separate comparison. A score of confidence has been designed for measuring those 3 criterions for the selection of a proper feature that can be represented as:

$$\begin{aligned}
&C_Score^t = Sign(\alpha) + Sign(\beta) + Sign(\gamma) \\
&\alpha = ratio^t \qquad (8) \\
&\beta = change_rate^t_{color} - change_rate^t_{SIFT} \\
&\gamma = \Delta^t_{color} - \Delta^t_{SIFT}
\end{aligned}$$

Where Sign (x) represents symbolic function. In *C-Score* definition, in the case where a score has been positive, the feature of the color is better compared to SIFT feature in a minimum of 2 criterions, color feature is selected in current frame to track and update the model In the opposite case, SIFT feature has been chosen. Overview of the suggested approach has been summarized in figure1.

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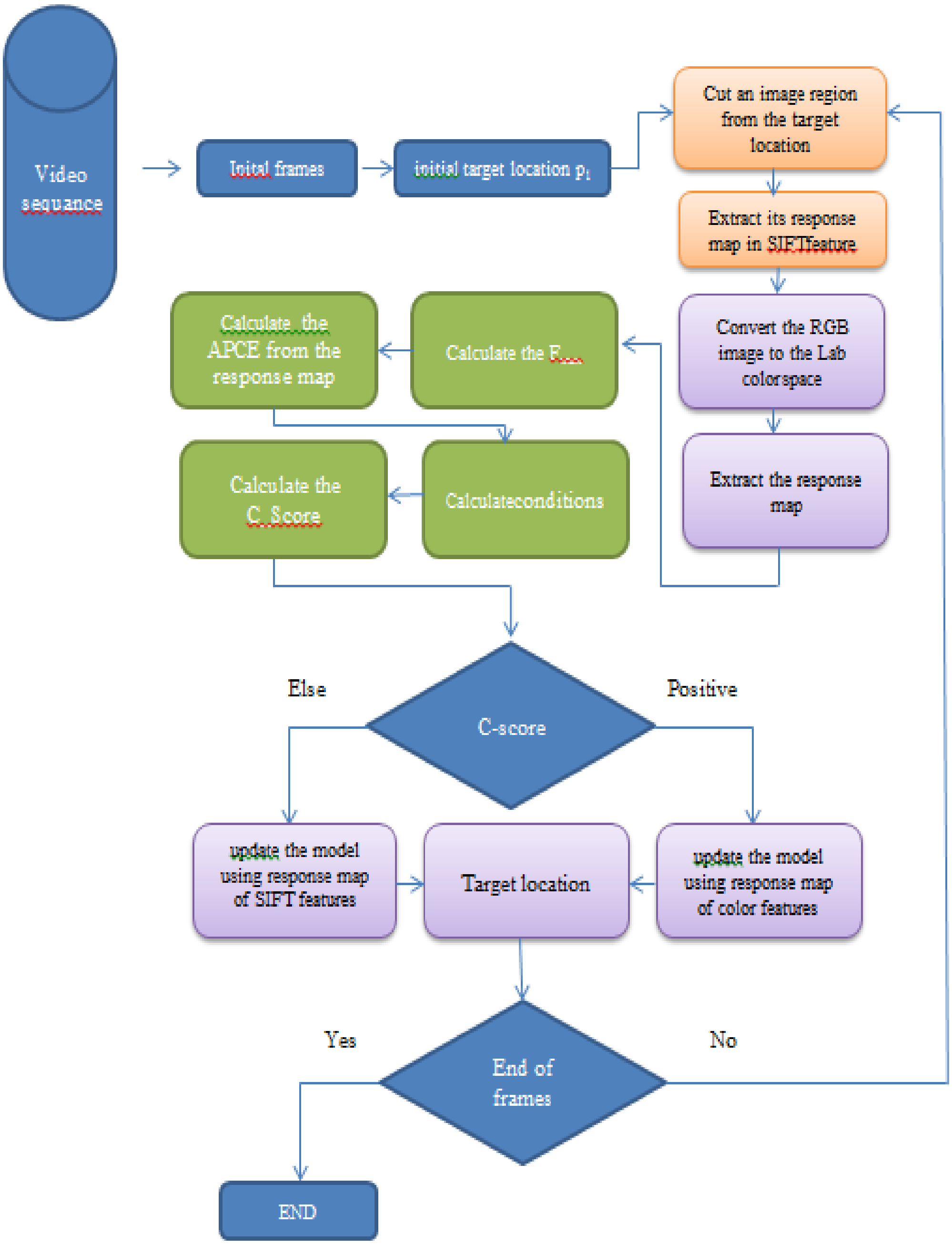

Fig1 A flowchart of the suggested algorithm of tracking

EXPERIMENTAL RESULT ANALYSIS

In the present section, the suggested approaches has been characterized on 2bench-mark data-sets, which are: OTB-13 [1] and OTB-15 [2], and compared to a number of the newest algorithms like the LMCF, Staple, [16], DSST, SRDCF [19] and KCF.

The evaluation standard that has been provided by benchmark OTB-15 was followed in this study, including 100 of the video sequences with a variety of the backgrounds and targets. In OTB-15, 4 indices have been utilized for the evaluation of all of algorithms that have been compared to 1-pass evaluation (OPE) like a center location error, bounding box overlap, overlap precision and distance precision. Trackers have been evaluated based on a result that has a 20-pixel error threshold for plots of precision For success plots, trackers have been assessed by scores of AUC. Figure2 illustrates the suggested method's performance as well as other filters of correlation on OTB15.

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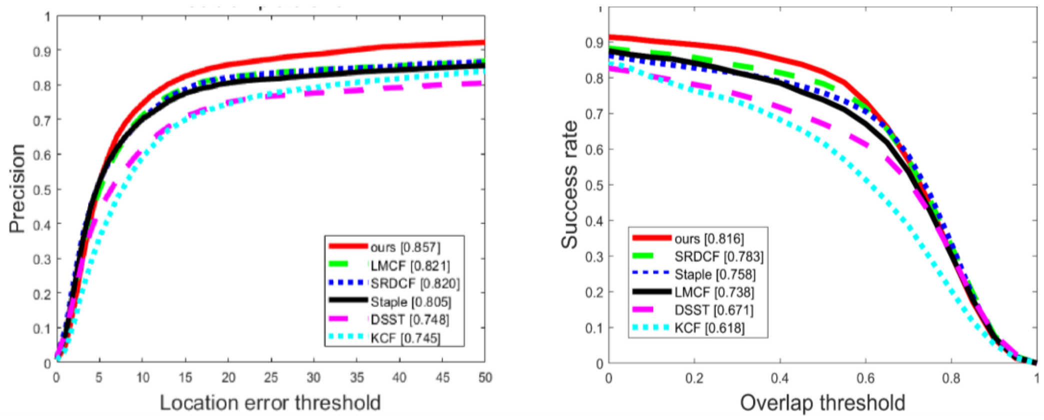

Fig 2 The plots of precision (on the left) and the success plots (on the right) of the OPE on OTB15 Numbers in legend show precisionscores as well as the AUC scores for every one of the trackers.

The suggested method performed considerably more efficiently in comparison with other approaches In the plot of the precision, the suggested tracker had performed 5% more efficiently compared to Staple algorithm This tracker showed as well that there has been a 6% enhancement compared to Staple in the success plot. For more specific analyses, the suggested tracker's efficiency may be influenced with a number of the issues, as can be seen from Figure 3.

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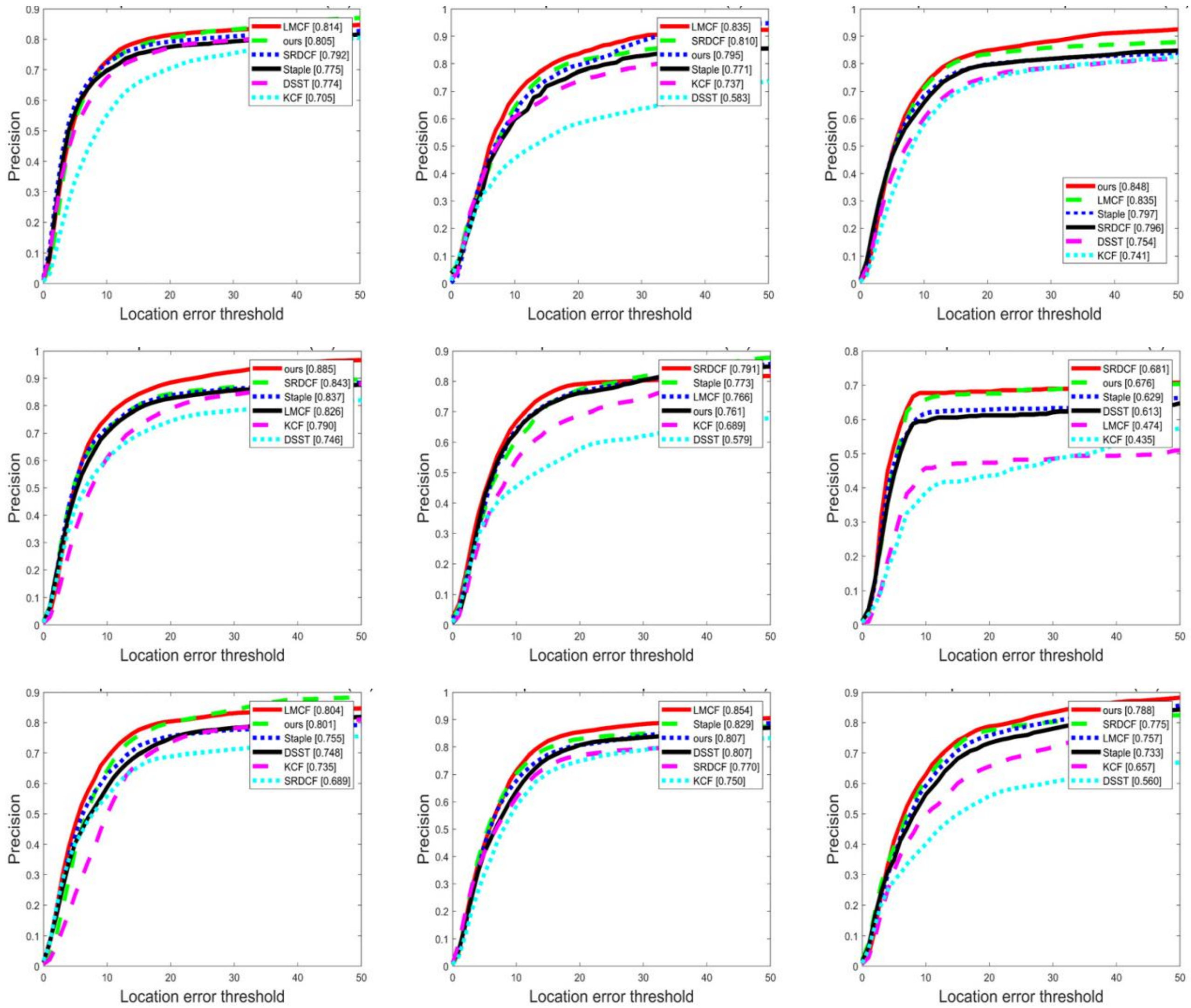

Fig 3 The success plots for 9 of the challenging attributes, which include the illumination variation, background clutter, deformation, occlusion, out-of-view, out-of-plane rotation, in-plane rotation, scale variation, and motion blur, The suggested tracker performs best or second best in nearly all of attributes.

It has shown the tracking approach's efficiency for a variety of the challenging attributes that have been provided in benchmark OTB15 like the Scale Variation (SV), Illumination Variation (IV), Deformation (DEF), Occlusion (OCC), In- Plane-Rotation (IPR), Motion Blur (MB), Out-of-View (OV), Out-of-Plane-Rotation (OPR), Background Clutters (BC), the suggested approach has been fount effective in DEF, BC, OPR, IV, and OCC in comparison with existing methods and more robust in comparison with trackers for the deformable objects.Due to the fact that the suggested approach's color feature is in the Lab space, it is capable of better recognizing changes of a different frame and improving the effect of the tracking compared to the other algorithms of the correlation filtering in the RGB colour space in the IV Moreover, in a case where a colour feature doesn't considerably change, SIFT feature might improve the effect of the tracking in DEF Figure4 illustrates results of different algorithms of tracking.

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Figure 4 Different representative frames of different tracking algorithms.

It doesn't fuse color features with SIFT features and enhances the effect of the tracking. The 3rd row represents deer sequence that denotes scenario of speedy motion In a video sequence the deer moves in very high speeds. The feature of the color has been automatically chosen as well by suggested approach. The 2nd row presents soccer sequence results that represent a scenario of the background clutters. From 70-th frame to the 113-th one, background colour turns red as well, which is why, APEC score of a color feature has been found lower compared to the score of a SIFT feature. The suggested tracker only utilizes SIFT features to track and produce more precise results of the tracking, whereas the rest of the trackers utilize the SIFT as well as the color features and tracking performance has been decreased. Those results have demonstrated that the suggested tracker is capable of handling a variety of the object categoriesthrough the adaptive selection of the features.

5. CONCLUSION

In the present study, for the purpose of improving the success and precision in the target tracking, an approach has been suggested for the adaptive selection of afeature based upon a score of confidence, which may be utilized for selecting the most proper feature for the tracking at every one of the frames in an adaptive manner.The adaptive selection of the features at frame level has been shown to have effectiveness for the improvement of tracking robustness. One of the disadvantaged of this approach is introducing additional confidence score computation, even though real time tracking might still be carried out. We will keep working on improving the suggested approach's speed in future works.

6. DECLARATION

This paper is a presentation of my original research work. Wherever contributions of others are involved, every effort is made to indicate this clearly, with due reference to the literature, and acknowledgement of collaborative research and discussions.

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