Non-Rigid Object Tracking Based on CamShift and Particle-Kalman Filter in Real-Time

Deogratias N. LUKAMBA[1], Abdul Salam Rasmi ASRAF ALI[1], Akshaykumar DUDHAGARA[1], Marc BLANCHON[2]

Abstract— **Real-time tracking implementation is the most challenging task in computer vision due to various constraints like occlusion, non-linear motion, illumination variation,invariant scaling, non-rigid object tracking, etc. A contributed algorithm for object tracking in real-time based on both deterministic and probabilistic methods has been implemented to enlighten the strongest point of each algorithm and cover their drawbacks. It combines both the accuracy of CamShift which is efficient for scale-invariant tracking with Particle-Kalman filtering which is robust to severe occlusion. We estimate the object's position, obtained by the CamShift tracker, which is treated as the observation for a Particle-Kalman filter to deal with the non-linearity problems. Experimental results show significant improvement concerning the recent techniques such as MeanShift-Kalman filter (MKF),CamShift -Kalman Filter (CKF), MeanShift-Particle-Kalman filter (MPKF) filter methods in terms of accuracy and execution time.**

Keywords: Non-rigid, scale invariant Object Tracking, MeanShift, CamShift, Particle-Kalman Filter

I. INTRODUCTION

Intelligence Surveillance System ideally deals with these four steps, object detection, classification, object tracking, and analysis. One of them, the object tracking, is a key and difficult task in computer vision research and intelligent video surveillance system. Many recent tracking algorithms were developed to cover multiple drawbacks that arise such as: MeanShift - Kalman Filter **(MKF)** , MeanShift Particle Filter **(MPF)** , MeanShift and Particle-Kalman Filter **(MPKF)** [1].

However, the technique, as mentioned earlier, is inefficient and presents some limitations to solve the problems of deformation, non-linear motion, partial or full occlusion as well as illumination variation [2]. Moreover, other challenges that make the tracking difficult to perform come from the target object's characteristics, when the target object has fast motion and moves in non-linear motion [3].

Due to these limitations, we are interested in implementing a robust scale-invariant object tracking system that will respond to the fore-mentioned problems. In this work, we intend to contribute to developing a robust object tracking algorithm by investigating the deterministic and probabilistic tracking algorithms and their characteristics to cover each algorithm's limitations.

[1]M2, International Master Programme in Computer Vision and Rocotics, University of Burgundy, 71200 - Le Creusot, France

[2] VIBOT ERL CNRS 6000, ImViA University of Burgundy Franche Comté Le Creusot, France

The paper is organized as follows. Section 2 briefly explains some related works. Section 3 introduces the proposed method used in this paper, explained in detail how to obtain the scale invariance from the CamShift and cover the severe occlusion with Particle-Kalman filter. Section 4 presents the results obtained from the proposed method followed by a brief discussion. Finally, Section 5 presents the conclusion and the future work of the project.

II. RELATED WORK

Several recent papers have worked on a single technique, and some researchers extended the idea to utilize the combination of more techniques in visual tracking. Still, the results were unsatisfied due to the inefficiency and limitations of the algorithm, perhaps. Our particular motivation will be to extract every single reliable point of each technique in order to cover their drawbacks. Our tracking algorithm will be divided into two classes: deterministic and probabilistic method.

To respond to the occlusion problem , a combined mean shift and Kalman filter **(MKF)** were introduced by [4], [5], [6]. Thanks to the Kalman filter algorithm, which always updates the estimation of the target object when occlusion occurs. As a drawback, the algorithm fails when dealing with the scale invariant object and non-linear motion since the Kalman filter ,which acts as a predictor, performs with linear motion and Gaussian noise. It is solved using Cam-Shift and Kalman filter **(CKF)** to cover the target object deformations scaling whereas [7], [8], [9],[10] proposed the combined mean-shift and particle filter , probabilistic method, will deal with the non-linearity and a random noise. In [10], using mean shift and particle that computes the mean-shift into each particle to shift them towards the local maximum. The **(MPF)** algorithm is considered to be robust to the fast-moving object and severe occlusion when the number of particles is reduced. Although using a few numbers of particles, the algorithm is still quite slow due to the number of iterations in the mean-shift as well as this drawback can be extended for the CamShift **(CPF)**.

Another technique that utilizes the combined mean-shift and particle-Kalman was proposed in [11]. The technique uses the mean-shift as a master tracker when there is no occlusion in the target object. When occlusion has occurred, or the mean-shift tracking result is not satisfied, the particle-Kalman filter will serve as a master tracker to update the tracking results. As a drawback , the algorithm fails in when dealing with non-linear fast moving object, background illumination variation [12] and scale object tracking.

To cope with the mean-shift and Particle Kalman filter challenges above mentioned, we contribute with the implementation of CamShift and Particle Kalman filter **(CPKF)**.The background information extracted from Hue of the HSV color based CamShift is used to define the target model. The CamShift filter is applied to each particles of the particle filter to estimate the local motion then to Kalman filter to perform global motion estimation.

III. Proposed Technique: CamShift and Particle-Kalman Filter

The proposed technique is combined CamShift and Particle-Kalman filter to respond to the problem of deformation and full-occlusion in a fast moving object tracking. The steps of the proposed method are explained as well as a flowchart is presented below.

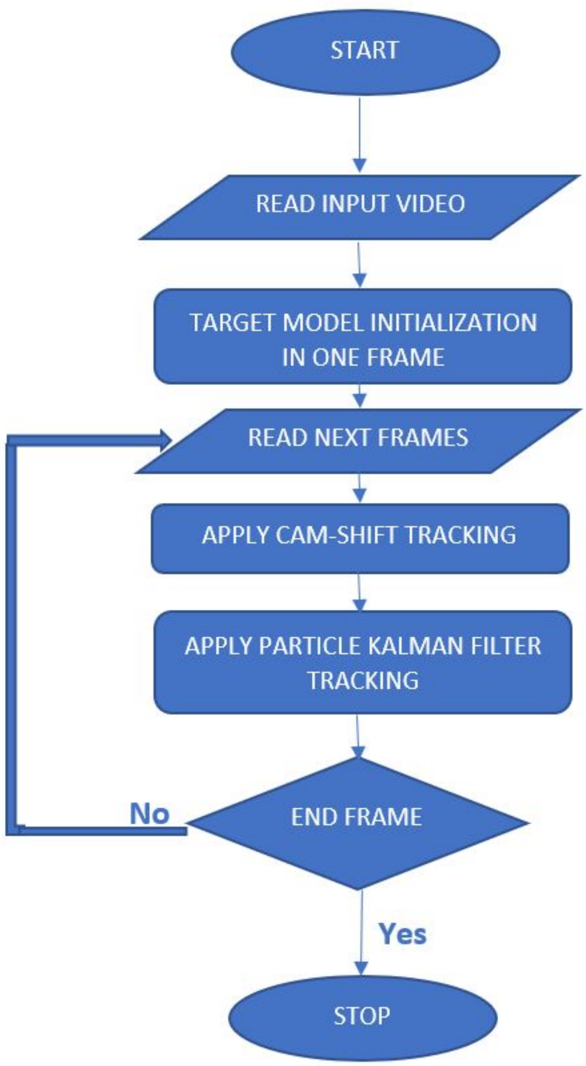


Fig. 1: Flowchart of the proposed technique

A. Initialization

We first manually initialize the target object starting from any given frame throughout the next frames of the video sequence. the target object is selected by drawing a small box as our region of interest. Additionally, to reduce the effect of illumination variation, Hue and Saturation from the HSV color space were employed to implement the weighted histogram given by the equation below:

$$q(u) = C\sum_{i=1}^{n}\left(\left\|\frac{x_c - x_i}{h}\right\|\right)^2 \delta\left(b\left(x_i\right) - u\right) \tag{1}$$

To cope with background illumination information, we defined the HSV Histogram thresholding. We select all Hue values (0-180) and saturation values in eliminating the values with very low saturation meaning that ignore the value that lacks useful colour information. That is given by:

$$k(r) = \begin{cases} ar & 1 < r \leq h \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

a = scaling factor and h = bandwidth of the new search window.

B. Applying the CamShift Algorithm

The system now can read the target object tracking in the next frame after initialize and setting up the HSV Histogram Thresholding. The camshift algorithm is used to improve the tracking object's performance in sudden velocity variation, and it is scaled invariant, but it is more affected when partial or full occlusion occurs.

Camshift stands for Continuously Adaptive Mean Shift. It is an updated of the Mean Shift algorithm that is done continuously to adapt or adjust to the ever-changing probability distribution of colors each frame change from the video sequence [13],[14],[15].

The following is the CamShift Algorithm:

1) Select an initial location of the MeanShift search window. The selected location is the target distribution to be tracked. Initial guess, $X = \begin{pmatrix} x \\ y \end{pmatrix}_{t=0}$
2) Calculate a color probability distribution of the region centred at the Mean Shift search window using equation (2).
3) Compute the zeroth moment (distribution area) and centroid location by :
   - Calculate M_{10}, M_{O1}, M_{OO} of the search window using the formula,

$$0^{th}\ moment,\ M_{00} = \sum_x \sum_y I(x,y)$$

$$1^{st}\ moment\ for\ x,\ M_{10} = \sum_x \sum_y xI(x,y)$$

$$1^{st}\ moment\ for\ y,\ M_{01} = \sum_x \sum_y yI(x,y)$$

4) Calculate the local mean at each time t^*,

$$\hat{X} = \left(\frac{M_{10}}{M_{00}}, \frac{M_{01}}{M_{00}}\right)\Bigg|_{t^*}$$

5) Calculate Mean-Shift-Vector,

$$\Delta X = \hat{X} - X$$

6) New search window will have its center at $\hat{X}_{t^*}$.
7) Increment t.
8) Loop until convergence, $\Delta X < threshold$.

Hence, The problem of scaling invariance is solved by finding the angle that provides the orientation in the long axis [14] of the tracking object:

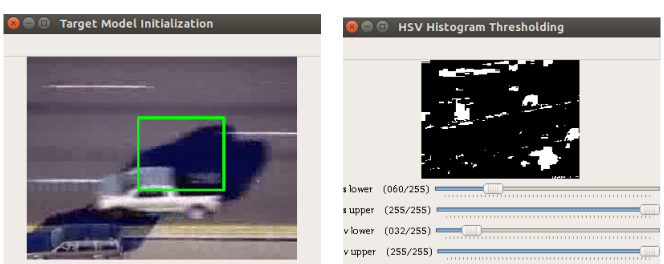
$$\theta = \frac{1}{2}\arctan\left[\frac{2\left(\frac{M_{11}}{M_{00}} - xy\right)}{\left(\frac{M_{20}}{M_{00}} - x^2\right) - \left(\frac{M_{02}}{M_{00}} - y^2\right)}\right]$$

C. Apply Particle-Kalman Filter

Followed by the Camshift Tracker, we pass the coordinates of the tracked Region of Interest (ROI) to the Particle-Kalman filter as an input; the camshift ROI is considered by the particle filter to define the number of particles, since it deals with non-linear motion and random noise. The particle filter output is then applied to the Kalman filter to reduce the number of particles thanks to its linearity. Hence, the particle will be limited to track the target object moving in a local view, whereas the Kalman filter in a global one. Therefore the occlusion and non-linear motion problems are resolved.

IV. Results & Discussion

In this section, we present the experimental results of our implementation. Figure 2 shows the target model initialization, which is performed manually by selecting a region with a bounding box. The HSV histogram of this model is computed, which serves as a reference for the CamShift (also MeanShift) Tracking.



(a) ROI (b) HSV

Fig. 2: Target Model Initialization and HSV Histogram Thresholding

In the figure, 3, the MeanShift result is shown where the bounding box is fixed, whereas in figure 4 the bounding box varies based on the scaling of the target model.

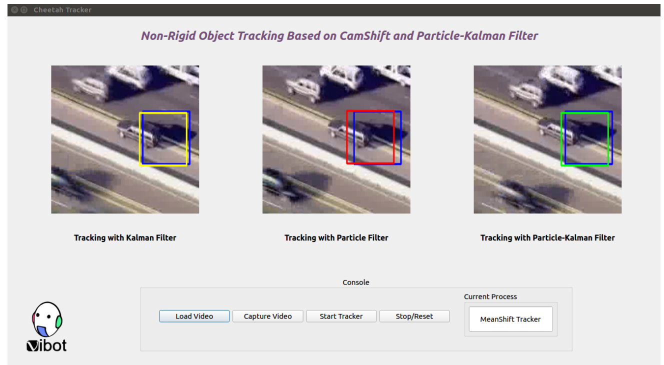


Fig. 3: Results using MeanShift

The blue, yellow, red and green bounding boxes correspond to CamShift Tracker, CamShift-Kalman Tracker, CamShift-Particle Tracker and CamShift-Particle-Kalman Tracker respectively.

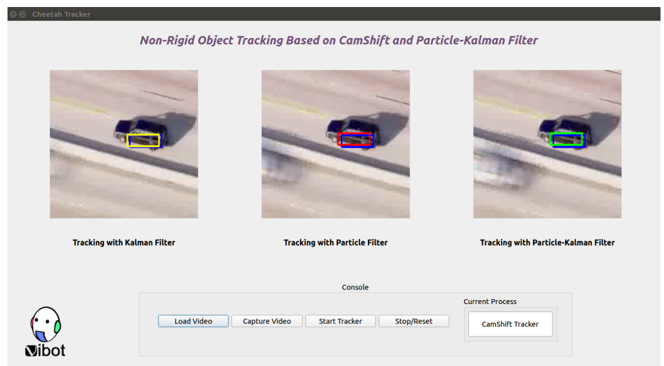


Fig. 4: Results using CamShift

Figures 5 & 6, shows the result of our implementation dealing with Full Occlusion and Fast Motion. It shows better tracking results compared to the existing algorithms.

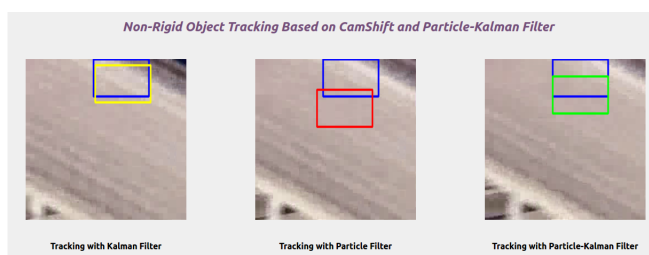


Fig. 5: Full Occlusion

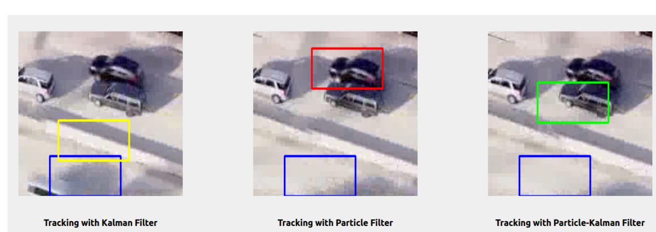


Fig. 6: Fast Motion

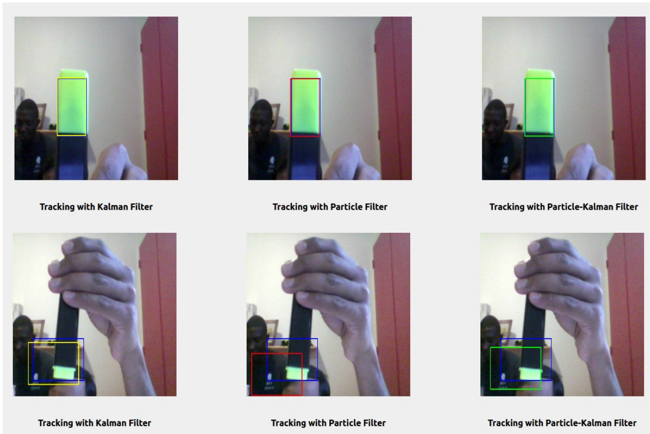


Fig. 7: False Tracking due to similar HSV Histogram

It can be seen from figure 7, how the algorithm fails if it finds a an object with similar colour distribution once when the target model is fully occluded. This is one of the drawback of the proposed system which will be discussed in the next section.

V. Conclusion & Future Work

We implemented an Algorithm to overcome the constraints of few existing Algorithms for Object Tracking. Firstly, CamShift (Continuously Adaptive MeanShift) is replaced with Traditional MeanShift Algorithm due to its Scale Invariance Property. Secondly, in the implemented Algorithm, combination of both Particle Filter and Kalman Filter is used instead of traditional Algorithms which uses either Particle Filter or Kalman Filter. Hence this Algorithm is robust to both Local and Global Variance (Particle Filter takes care of Local Variance and Kalman Filter takes care of Global Variance).

Combining both CamShift Tracker and Particle-Kalman Filter gives more accurate tracking results than the existing Algorithms. It is Robust to fast and non-linear motion, robust to Occlusion and Scale Invariant, however the proposed algorithm has its own drawbacks. Like other Algorithms, it fails due to drastic variations in Illumination conditions and similar Color interference (object is occluded by other object which has similar color distribution). To overcome these drawbacks CamShift Algorithm can be upgraded for tracking multiple features like Textures, Edges, HSV Weighted Histograms, Local Binary Patterns, etc.

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