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ROI Based Video Object Tracking Using Mean Kernel Profile of Histogram

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Abstract: Object Tracking is one of the most challenging subjects in the field of computer vision, surveillance, traffic monitoring, video compression etc. The aim of object tracking is to find a moving object in a video frames sequence. Normally a video tracking system combines three stages of data tracking; object extraction, object recognition & tracking. We propose an approach for tracking object in a single frame in which a centre point of object is taken as focus component. The histogram profile based object representations are updated by changing kernels. To enhance localization of the tracked object some region bounding structure information is added to the method of tracking. This method is successfully adjusted with moving camera, Partial occlusions and changing scale and orientation of target have overcome the need of background subtraction making it more efficient. Some main applications are: surveillance application, control application and analysis application.

Keywords: Kernel, localization, mean, kalman, histogram.

1. INTRODUCTION

Visual tracking is an important task within the field of computer vision. The proliferation of high-end computers, the availability of high quality video cameras, and the increasing need for automated video analysis have generated a great deal of interest in visual tracking algorithms. The state of this art has advanced significantly in the past 30 years [1]. Generally speaking, the use of visual tracking is pertinent in the tasks of motion-based recognition, automated surveillance, video indexing, human–computer interaction and vehicle navigation, etc. Object tracking in video sequences is an important topic in the field of computer vision and various research fields. Object tracking aims at deriving the trajectory over time of moving object in video sequences [5]. Object tracking has various applications in the areas like security, surveillance, clinical applications, education, entertainment, biomechanical applications, human robot interaction etc.

There are two key steps in object tracking process:

- Object detection: detection of an object in a given scenario.
- Object tracking: frame by frame tracking of object.

Tracking of objects is very complex in nature due to several problems. Following difficulties come during object tracking:

- The object's shape and size may vary from frame to frame.
- Partial and full object occlusion.
- Presence of noise and blur in video.
- Luminance and intensity changes.
- Object's abrupt motion.

To perform tracking in video sequences, an algorithm analysis sequential video frames and outputs the movement of target between the frames. Many tracking algorithms have been proposed so far. These object tracking methods are classified according to their tracking behaviour.

2. VISUAL TRACKING PROBLEM

Visual tracking, in general, is a very challenging problem due to the loss of information caused by the projection of the 3D world on a 2D image, noise in images, cluttered-background, complex object motion, partial or full occlusions, illumination changes as well as real-time processing requirements, etc. In the early years, almost all visual tracking methods assumed that the object motion was smooth and no abrupt appearance change. However, tremendous progress has been made in recent years. Some algorithms can deal with the problems of abrupt appearance change, and drifting, etc. To build a robust tracking system, some requirements should be considered.

2.1Robustness

Robustness means that even under complicated conditions, the tracking algorithms should be able to follow the targeted object. The tracking difficulties may be cluttered background, partial and full changing illuminations, occlusions or complex object motion.

2.2Adaptivity

Additional to various changes of the environment that an object is located in, the object itself also undergoes changes. This requires a steady adaptation mechanism of the tracking system to the actual object appearance.

2.3Real-time processing

A system that needs to deal with live video streams must have high processing speed. Thus, a fast and optimized implementation as well as the selection of high performance algorithms is required. The processing speed depends on the speed of the observed object, but to achieve a smooth output video impression for human eyes, a frame-rate of at least 15 frames per second has to be established.

3. TRACKING METHODS

Point tracking can be defined as the correspondence of detected objects represented by points across the frames [8]. There are two methods of correspondence methods namely – deterministic and statistical methods [8]. Point Tracking is a difficult problem particularly in the existence of occlusions, false detections of object. Recognition of points can be done simply by thresholding, and identification of these points [9].

First step for background subtraction is background modelling. It is the core of background subtraction algorithm. Background Modeling must be sensitive enough to recognize moving objects [10]. Background Modeling is used to yield reference model. This reference model is used in background subtraction in which each video sequence is compared against the reference model to

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determine possible Variation. The variations between current video frames to that of the reference frame in terms of pixels signify existence of moving objects [12]. Currently, mean filter and median filter [8] are widely used to realize background modeling. The background subtraction method is to use the difference method of the current image and background image to detect moving objects, with simple algorithm, but very sensitive to the changes in the external environment and has poor anti-interference ability. However, it can provide the most complete object information in the case background is known.

4. PROPOSED TRACKING METHOD

An algorithm that iteratively shifts a data point to the average of data points in its neighbourhood which is similar to clustering and useful for clustering, mode seeking, probability density estimation, tracking, etc. Mean-kernel tracking tries to find the area of a video frame that is locally most similar to a previously initialised model. The image region to be tracked is represented by a histogram. It contain target model and target candidate. To characterize the target colour histogram is chosen. Target model is generally represented by its probability density function (pdf). Target model is regularized by spatial masking with an asymmetric kernel.PDF is calculated through kernel density estimation

$$f(x) = \frac{1}{\eta h d} \sum n\, i = 1\, K(x - xi\, /\, h) \qquad (1)$$

Here h is the bandwidth of the kernel, n is the total number of point in the kernel. In target representation target is selected manually in first frame and the pdf of the second frame is calculated consecutively. The presence of the continuous kernel introduces interpolation process between location and image. A similarity function defining the correlation between target model and target candidate generally gives the distance between target model and target candidate, the distance should have metric structure. It is specified in the form of distance between two discrete distributions given by Bhattacharya coefficient given as

$$d = \sqrt{1 - \rho(y)} \qquad (2)$$

Here p(y) is referred to as Bhattacharya coefficient. Kernel based mean shift is basically rely on the spectral features of image, which create problem when the same colour objects comes in same frame and produce localization error.

5. BHATTACHARYYA COEFFICIENT

The similarity function defines a distance among target model and candidates. To accommodate comparisons among various targets, this distance should have a metric structure. We define the distance between two discrete distributions as

$$d(y) = \sqrt{1} - \rho[p(y), q], \qquad (3)$$

Where, we chose

$$p(y) = \rho[p(y), q] - \sum_{u-1}^{m} \sqrt{pa(y)qa} \qquad (4)$$

the sample estimate of the Bhattacharyya coefficient between *p* and *q*. The Bhattacharyya coefficient is a divergence-type measure [49] which has a straightforward geometric interpretation. It is the cosine of the angle between the *m*-dimensional unit vectors $(\sqrt{p_1} \ldots\ldots \sqrt{p_m})^T$ and $(\sqrt{q_1} \ldots\ldots \sqrt{q_m})^T$. The fact that and are distributions is thus explicitly taken into account by representing them on the unit hypersphere. At the same time we can interpret as the (normalized) correlation between the vectors $(\sqrt{p_1} \ldots\ldots \sqrt{p_m})^T$ and $(\sqrt{q_1} \ldots\ldots \sqrt{q_m})^T$.

6. KERNEL MINIMIZATION

Minimizing the kernel cluster distance (3) is equivalent to maximizing the Bhattacharyya coefficient *p(y)*. The search for the new target location in the current frame starts at the location *y0* of the target in the previous frame. Thus, the probabilities $\{p_a(y0)\}_{u-1\ldots m}$ of the target candidate at location *y0* in the current frame have to be computed first. Using Taylor expansion around the values $p_a(y0)$, the linear approximation of the Bhattacharyya coefficient is obtained after some manipulations as

$$\rho[p(y), q] \approx \frac{1}{2} \sum_{u=1}^{m} \sqrt{pa(y0)qa} + \frac{1}{2} \sum_{u=1}^{m} pa(y) \sqrt{\frac{qa}{pa\,(y0)}} \qquad (5)$$

The approximation is satisfactory when the target candidate $\{p_a(y)\}_{u-1\ldots m}$ does not change drastically from the initial $\{p_a(y_0)\}_{u-1\ldots m}$, which is most often a valid assumption between consecutive frames. On the basis of target model $\{q_a\}_{u=1\ldots m}$ and its location y_0 in the previous frame.

1. Initialize the location of the target in the current frame with y_0, compute $\{p_a(y_0)\}_{u=1\ldots m}$,

and evaluate

$$\rho[p(y0), q] = \sum_{u=1}^{m} \sqrt{pa(y0)qu}$$

2. Derive the kernel weights $\{u_i\}_{i-1\ldots m}$, .

3. Find the next location of the target candidate according to (5).

4. Compute $\{p_a(y_1)\}_{u-1\ldots m}$, and evaluate

$$p[p(y1), q] = \sum_{u-1}^{m} \sqrt{pa(y1)qu}$$

5. While $p[p(y_1),q] < p[p(y_0),q]$

   Do $y_1 - \frac{1}{2}(y_0+y_1)$

   Evaluate $p[p(y_1), q]$

6. If $\| y_1 - y_0 \| < t$ Stop.

Otherwise, Set y_0 to y_1 and go to Step 2.

The tracking algorithm will stop scanning for object if the shifting means will not have considerable difference and will end the loops depending upon the completion requested no. of frames

7. PROPOSED MODEL DIAGRAM

In first frame ROI is selected manually in the target window then analyzed by the mean shift.
Then application of histogram profile is introduced and calculation of weighted values is done.
Then the value of the current weighted values is taken and sent to the mean-kernel algorithm.
The mean-kernel then processes the updating path of the object in every frame and then stores the distance and location measure for all frames of video.

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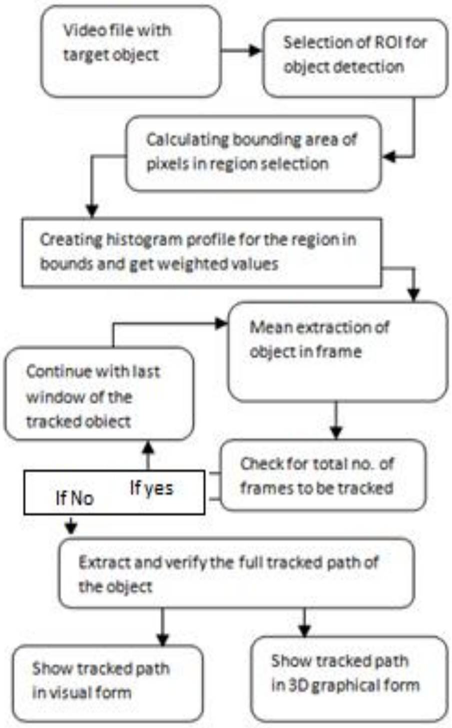
8. FLOW DIAGRAM



Finally when the algorithm stops the tracking data is retrieved and a 2D plot shows the truth of tracking process.

If kernel tracking is not working smoothly then low localization is achieved. Low localization means objects are moving out of the target window and window is unable to shift its centre with it. In this case we alter the window size and change its spectral feature in order to boost the accuracy of the process.

9. RESULTS

Tracking for objects with changing background

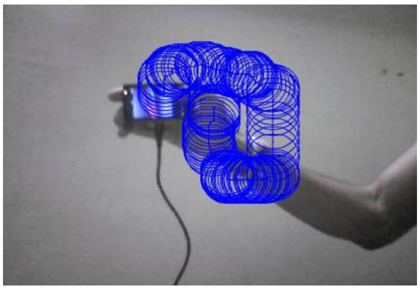


Fig.1 Video frame with tracked path

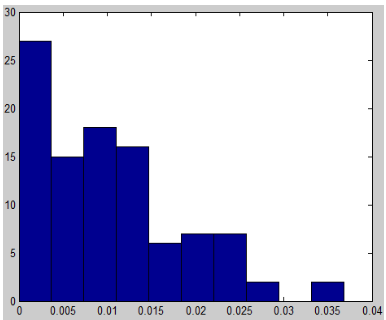


Fig.2 Histogram profile for tracking of object
Tracking Time: 34 Seconds

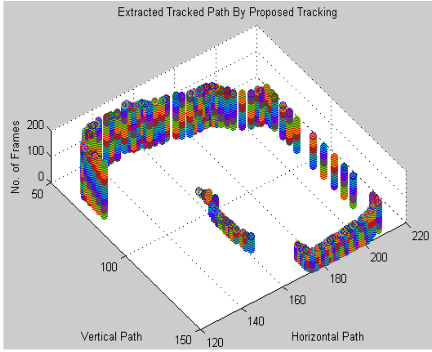


Fig .3 Extracted Tracked Path by Proposed Tracking

Tracking for objects with still background

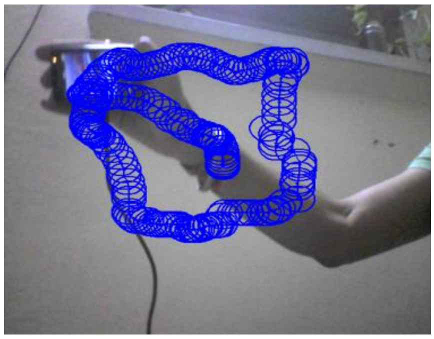


Fig.4 Video frame with tracked path

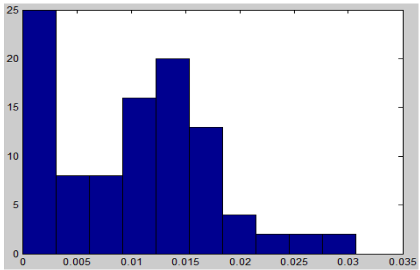


Fig.5 Histogram profile for tracking of object

Tracking Time: 123 Seconds

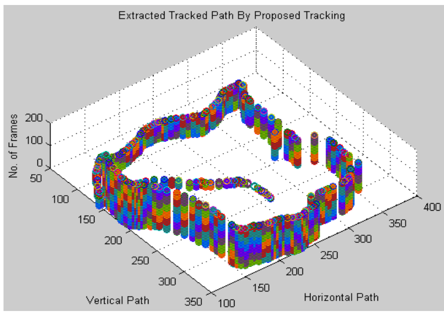


Fig .6 Extracted Tracked Path by Proposed Tracking

Tracking for objects with still background (Base algorithm)

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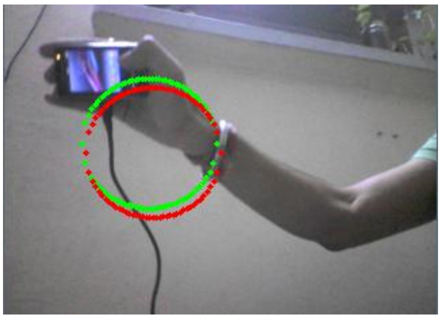

Fig.7 Video frame with tracked path

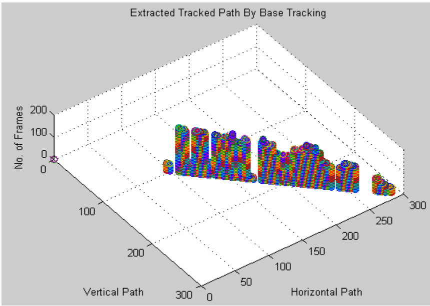

Fig.8 Tracked object Path

Tracking Time: 188 Seconds

The mean kernel based object tracking method has performed on still camera as well as moving camera video files above. We find that in proposed method there is less tracking error then past approaches where we use background subtraction and filtering mechanisms to track. Both vertical and horizontal directional coordinates are calculated for the object present in the frame with dynamic histogram mean kernel shift and then the corrected approx value is given by our method.

Method	Size of frame	Tracked no. of frames	External editing
Base	256x256	200	None
Proposed	256x256	200	None

10. CONCLUSION

In proposed method of tracking objects and the low appearance with partial occlusions is solved. This method is efficient and robust as comparison to many other mean shift and various other programs in many applications like visual surveillance, human computer interaction, traffic monitoring, vehicle navigation etc. Future work is done towards enhancing the capabilities of trackers by making them more robust to track object in more noisy condition like full occlusion, changing light condition complex object motion etc .The adaptive tracking based scaled window will also be proposed.

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