

Robust Visual Target Tracking Via Nearest Sequential Boundary Pattern

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Abstract— Video tracking is the modernized technology used for retrieving the target object from the frame. The representation of the target is the necessary component for a robust tracker. During the tracking process several factors make the errors significantly large, which leads to the drift in the target. This paper presents a propose a novel method for tracking the target regions from the video frame. Nearest Sequential Boundary Pattern (NSBP) is a new method used for the extraction of background and retrieval of pattern from moving object. The extracted target is used for classifying the regions from the target using the Relevant Pattern Classification (RPC) algorithm. It is used for matching the grid as the tracked region and provides the binary label for separating the background and the foreground. Then the target is tracked using the blob based extraction technique. Then the performance of the video tracking system is analyzed using several parameters such as sensitivity, specificity and accuracy.

Keywords—Relevant Pattern Classification (RPC), Nearest Sequential Boundary Pattern (NSBP), Video tracking, Video processing

I. INTRODUCTION

An essential component in multimedia application is the video because of rich content. The development of robust tools is the challenging task in computer vision processes includes video indexing, browsing or searching. The processes such as the segmentation of foreground from the background, shadow removal and the target tracking are based on the non-changing background of surveillance area. The tracking of target in video frames is a challenging problem in computer vision because of the appearance of the target environment, illumination changes and the partial occlusions[1]. The aerial imagery is generally considered to be harder than the traditional tracking system due to the problems associated with a moving platform, which includes the gimbals based stabilization errors, and Geo-registration errors. Tracking is defined as the problem of approximating the path of an objects

in the image plane as it is moving around a scene. The task of the visual tracking is to estimate the motion states of the target in successive frames by giving an initial state. The accumulated error during the learning process is the major factor, which influence the tracking performance.

A. Video Tracking

The captured video frames are converted and saved in the digital format. After the estimation of suitable target area, the segmentation process segments the target area from the original video frame. The features from the extracted target area are obtained using the feature extraction algorithm. By exploiting the extracted features, the classification algorithm classifies the video frames and identifies the object for enabling the tracking operation.

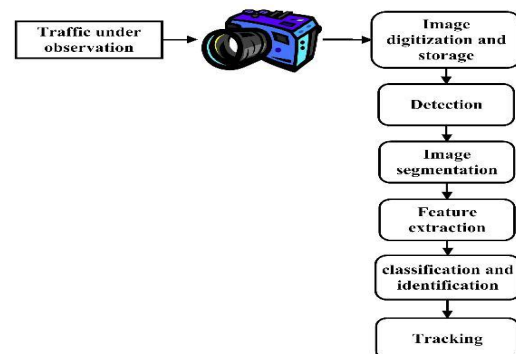


Fig 1.General Flow Diagram of Video Tracking

In this paper, an effective target tracking system in videos using various preprocessing, feature extraction and classification techniques are proposed.

This rest of this paper is organized as follows, Section II illustrates the various preprocessing algorithms, feature extraction and the classification techniques for an efficient

target tracking system. Section III describes the proposed work, and the paper is concluded in section IV.

II. RELATED WORK

Video Tracking or target tracking system is the process of tracing the objects, which are moving over time. The main

objective of video tracking is to associate the target objects in consecutive video frames. Table I depicts comparative and survey of video tracking and methods.

TABLE I LITERATURE SURVEY

| Author/Year | Paper | Method | Advantages | Disadvantages |
|-----------------------------------------------------------|----------------------------------------------------------------------------------------------------|---------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------|
| L. Wang, T. Liu, G. Wang, K. L. Chan, and Q. Yang | Video tracking using learned hierarchical features | A hierarchical feature learning algorithm for object tracking | The adapted features were robust to both complicated motion transformations and appearance changes of specific target object. | The performance of the system must be improved |
| L. Lin, Y. Lu, Y. Pan, and X. Chen | Integrating graph partitioning and matching for trajectory analysis in video surveillance | Markov Chain Monte Carlo algorithm | Recover the trajectories against occlusion, interruption and background cluster | For the improvement in computational efficiency the parallel implement for MCMC based interference to be designed |
| A. Makris and C. Priour | Bayesian multiple-hypothesis tracking of merging and splitting targets | Bayesian MTT model and a two-step MHT algorithm | Tracking accuracy and computation efficiency was improved | The model was extended to raw sensor data to avoid the artifacts caused by the threshold and the ellipse fitting procedure. |
| T. Bai and Y. Li | Robust visual tracking using flexible structured sparse representation | Block Orthogonal Matching Pursuit (BOMP) algorithm, | The accuracy obtained from the system was more based on the qualitative and quantitative results | Presence of similar object or the occlusion in the scene |
| C. Park, T. J. Woehl, J. E. Evans, and N. D. Browning | Minimum Cost Multi-Way Data Association for Optimizing Multitarget Tracking of Interacting Objects | Polynomial time solution approach | It provided the integral solution and minimized duality gap. | Corruption occurred in the driven base. |
| X. Li, A. Dick, C. Shen, A. Van Den Hengel, and H. Wang | Incremental learning of 3D-DCT compact representations for robust visual tracking | 3-dimensional Discrete Cosine Transform (DCT) | It generated the compact energy spectrum for the similar appearance. | Presence of similar object or the occlusion in the scene introduced the failures in the discrimination of target and background |
| K. Zhang, L. Zhang, and M.-H. Yang | Real-time object tracking via online discriminative feature selection | Multiple Instance Learning (MIL) | computation efficiency was improved | The existence of complicated factors made the accumulated error leads to tracking drift |
| S. Liwicki, S. Zafeiriou, G. Tzimiropoulos, and M. Pantic | Efficient online subspace learning with an indefinite kernel for visual tracking and recognition | Extension of Kernal PCA from Hilbert to Krien space | The formulation of KPCA in krien space is independent of pre-images. | The high dimensionality in KPCA affected the tracking performance |
| Y. Li, W. Jia, C. Shen, and A. van den Hengel | Characterness: an indicator of text in the wild | Markov Random Field (MRF) model | accuracy and efficiency was improved | The variation in illusion and contrast are the major problem in text detection and tracking |
| D. Wang, H. Lu, and M.-H. Yang | Online object tracking with sparse prototypes | Combination of PCA and sparse representation | Used for the online tracking of objects. | The problems in Visual tracking are less robustness and accuracy |

III. NEAREST SEQUENTIAL BOUNDARY PATTERN

There are several techniques reviewed in the previous Section and the drawbacks of many techniques are also listed in the related work section. In order to extract the back ground and

to retrieve the patterns from a video, a back ground extraction technique such as the Nearest Sequential Prediction (NSP) method and Frame Boundary Pattern (FBP) are proposed. This section illustrates the flow of the proposed work, which is

depicted in Fig. 2. The overall flow of the proposed model for the extraction of the patterns from the video frame and the removal of shadows are described in detail. It consists of the following stages such as:

- Preprocessing
- Pattern Extraction
- Classification
- Tracking of Target

A. Preprocessing:

Preprocessing is the initial step of video processing in which the noise or the shadow regions are removed using filtering mechanisms. In this Phase the given input frames are filtered using the Enhanced AMF (Adaptive Median Filter) for smoothening effect.

B. Nearest Sequential Prediction

In this technique, center value of the pixel in each frame is taken. Averaging center pixels noisy pixels are identified. In this model relevancy between the intensity of the neighborhood pixels is referred. It is predicted from difference of previous and present intensity pixels. Finally it forms the chain link of pixels information from the shadow of the background and the foreground detected. The shadow of the image is suppressed by applying the histogram equalization.

C. Frame Boundary Pattern

In this phase attribute vectors are extracted. Frame is converted into a grid arrangement and from the grid formation, the difference in pixels are calculated in several projection of the angle.

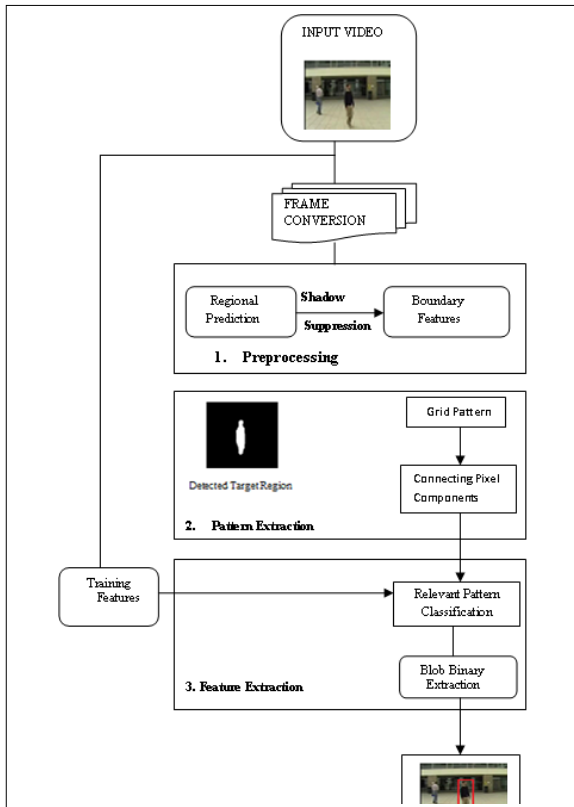


Fig 2 Overall Flow of the Proposed Video Tracking

The histogram attribute vectors are estimated for representing the target frame, which gives the information regarding the moving object. The feature values are used accordingly for extracting the target object from a frame.

D. Relevant Pattern Classification

Relevant Pattern Classification (RPC) algorithm is proposed for tracking the target object from the given video. The extracted features or the patterns are fused and classified using the RPC algorithm. The classification provides the label for the frames using the 0 or 1. The target region, which is detected from the video is marked as 1 and the other regions in the frame is marked as 0, which forms the targeted region effectively classified using the RPC classification. A novel technique is proposed for tracking the target. The target region is applied with the bounding box for representing the tracked target region. The moving objects in the video frame, which is classified using the RPC algorithm are considered as the blobs. The blobs are the region of targeted object in the frames. Then the bounding box is applied for each and every blob in the video frame.

IV. ALGORITHM

A. STEPS

1. Input video frame
2. Preprocessing for Filtering process.
3. Extract chain link formation
4. Detach shadow affected region.
5. Enhance the pixel intensity on the shadow region.
6. Normalize the image in each frame.
7. Formation of Grid arrangement
8. FB Pattern extraction for feature selection.
9. RPC for background prediction and target region using Track the object.

V. EXPERIMENTS AND RESULTS

The proposed method is implemented with windows 8 operating system with Core-i3 and 2 GB

A. Dataset

In this research, there are two videos that are used to evaluate the proposed method. we have taken football video and traffic from CAVIAR dataset.



Fig 3 Input video

B. Experimental Results

The utilization of sequences is 24 frames /secs with the size of 384X288. The average length of the video sequence is about 100s and the entire datasize is 210MB in MPEG4-format.



Fig 4 Preprocessed Frame



Fig 5 Pattern Selection

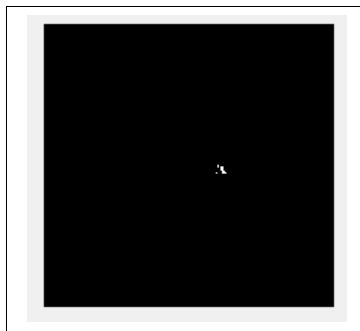


Fig 6 Background Substraction



Fig 7 Target tracking

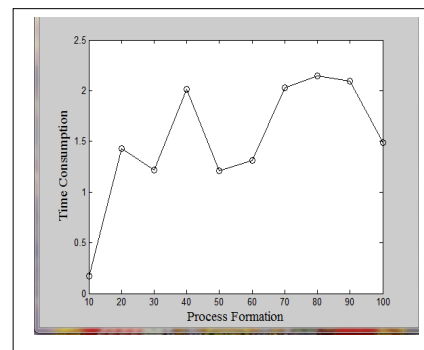


Fig 7 Time consumption

C. Analysis Parameters

The overall performance of methodologies are assessed by means of measuring the True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) computations obtained on comparing the images being processed and those original images acquired from a video sequence. The proposed work is compared with several parameters such as:

TP (true positive):

detected regions that correspond to moving objects,

FP (false positive):

detected regions that do not correspond to a moving object,

FN (false negative):

moving objects not detected.

a) Specificity

It is the measure of the negatives, which are identified correctly. This parameter is used for analyzing the propose work. It is expressed using the following equation

$$\text{Specificity} = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}}$$

b) Sensitivity

It is the measure of the positives, which are identified correctly. This parameter is used for analyzing the propose work. It is expressed using the following equation (2).

$$\text{Sensitivity} = \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false positives}}$$

c) Accuracy

It is the other metric used for analyzing, which is defined as the measure or the test method. It measures, what it is supposed to measure. It is represented as below:

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn} \quad (3)$$

d) Precision

Precision metric is defined as the value assessed between ratios of the associations between any two patterns retrieved at a single instance of time.

$$Precision = \frac{TP}{TP + FP}$$

NSBP model provides the precision value of 96.98%. The proposed method has a precision value of 33.7% improvement compared to HMRMF (64.2%)

e) Recall

The proportional value inferred from those associated patterns and those retrieved patterns .

$$Recall = \frac{TP}{TP + FN}$$

NSBP provides the recall value of 96.7 .The proposed method offers 32.99% improvement compared to HMRMF (64.8%)

f) F-Measure(F)

The association inferred between precision and recall is defined as F1-measure.

$$F = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

g) Complexity Analysis

The proposed method has the complexity depends on the patterns (P), and the Boundary grid cells (B) like O(P+B) which is less compared to the existing models Table I illustrates the comparative analysis between precision, recall and F1 measure observed on realizing GVO and NSBP on the standard dataset.

TABLE II COMPARATIVE ANALYSIS

| Tracking methods | Precision | Recall | F1 measure |
|------------------|-----------|--------|------------|
| ZHU | 0.549 | 0.953 | 0.688 |
| NSBP | 0.9793 | 0.9758 | 6.19% |

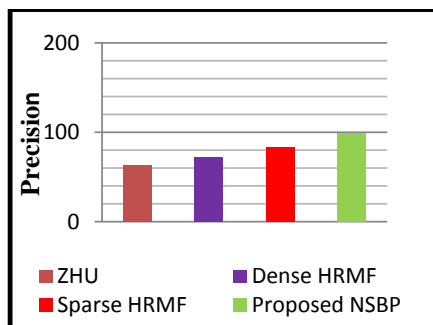


Fig 8 Precision value

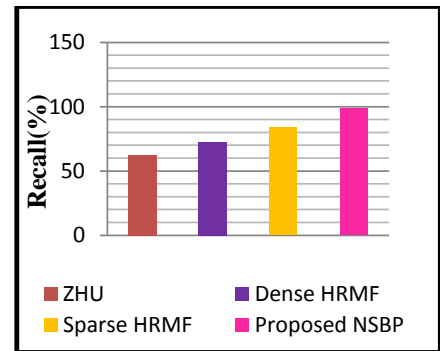


Fig 9 Recall value

TABLE III SUCCESS AND FAIRE RATE

| Tracking methods | Success rate | Failure rate |
|------------------|--------------|--------------|
| <i>CT</i> | 85.92 | 10.7 |
| <i>Struck</i> | 87.32 | 11.7 |
| <i>PartT</i> | 54.93 | 23.3 |
| <i>MVS</i> | 90.14 | 6 |
| NSBP | 97.95 | 3.86 |

VI. CONCLUSION

In this paper, several techniques such as preprocessing, pattern extraction, classification techniques are analyzed and surveyed. Its disadvantages of the various techniques in each paper are studied. The employment of texture pattern analysis in proposed work improved the robustness over the sudden illumination changes and the dynamic background. The comparison of proposed Nearest sequential boundary pattern with the existing segmentation techniques regarding the accuracy, precision, recall, F-measure, success and error rate assured the effectiveness in visual tracking applications. The integration of correlation-based filters with the adaptive shape variations to be considered as the future work for further improvement in tracking performance.

References

- [1] H. S. Parekh, D. G. Thakore, and U. K. Jaliya, "A survey on object detection and tracking methods," *International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCCE)*, vol. 2, pp. 2970-2978, 2014.
- [2] S. Yao, Z. Shunli, and Z. Li, "Robust Visual Tracking via Sparsity-Induced Subspace Learning," *IEEE Transactions on Image Processing*, vol. 24, pp. 4686-4700, 2015.
- [3] X. Zhang, W. Hu, N. Xie, H. Bao, and S. Maybank, "A robust tracking system for low frame rate video," *International Journal of Computer Vision*, vol. 115, pp. 279-304, 2015.
- [4] D.Mohanapriya,Dr.K.Mahesh "A Comparative Analysis of Video Tracking Techniques" *International Journal for Modern Trends in Science and Technology*, Volume: 03, Issue No: 05, May 2017.
- [5] L. Wu, P. Shivakumara, T. Lu, and C. L. Tan, "A New Technique for Multi-Oriented Scene Text Line Detection and Tracking in Video," *IEEE Transactions on Multimedia*, vol. 17, pp. 1137-1152, 2015.

- [6] N. Liu, H. Wu, and L. Lin, "Hierarchical ensemble of background models for PTZ-based video surveillance," *IEEE Transactions on Cybernetics*, vol. 45, pp. 89-102, 2015.
- [7] T. Bai, Y.-F. Li, and X. Zhou, "Learning local appearances with sparse representation for robust and fast visual tracking," *IEEE Transactions on Cybernetics*, vol. 45, pp. 663-675, 2015.
- [8] D.Mohanapriya, Dr.K.Mahesh, "A Survey on Video Object Tracking System", *International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)*, Vol.3, Special issue 20, April 2016, pp.474-479.
- [9] C. Park, T. J. Woehl, J. E. Evans, and N. D. Browning, "Minimum cost multi-way data association for optimizing multitarget tracking of interacting objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 37, pp. 611-624, 2015.
- [10] . Zhang, X. Yu, Y. Sui, S. Zhao, and L. Zhang, "Object tracking with multi-view support vector machines," *IEEE Transactions on Multimedia*, vol. 17, pp. 265-278, 2015.
- [11] S. Liwicki, S. P. Zafeiriou, and M. Pantic, "Online Kernel Slow Feature Analysis for Temporal Video Segmentation and Tracking," *IEEE Transactions on Image Processing*, vol. 24, pp. 2955-2970, 2015.
- [12] S. Salti, A. Lanza, and L. Di Stefano, "Synergistic Change Detection and Tracking," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, pp. 609-622, 2015.
- [13] L. Wang, T. Liu, G. Wang, K. L. Chan, and Q. Yang, "Video tracking using learned hierarchical features," *IEEE Transactions on Image Processing*, vol. 24, pp. 1424-1435, 2015.
- [14] H. Liu, S. Chen, and N. Kubota, "Intelligent video systems and analytics: a survey," *IEEE Transactions on Industrial Informatics*, vol. 9, pp. 1222-1233, 2013.
- [15] D.Mohanapriya, Dr.K.Mahesh, "Robust Video Tracking System with shadow suppression based on Feature Extraction", *Australian Journal of Basic and Applied Sciences*, Vol.10, No.11 (July), 2016 pp 307-311.,
- [16] S. Ballesta, G. Reymond, M. Pozzobon, and J.-R. Duhamel, "A real-time 3D video tracking system for monitoring primate groups," *Journal of neuroscience methods*, vol. 234, pp. 147-152, 2014.
- [17] D.Mohanapriya, Dr.K.Mahesh, "Video Tracking System by suppressing shadow and Feature Extraction- A Review", *International Journal of Computer Engineering and Applications(IJCEA)*, Vol.10, No 6 ,June , 2016.
- [18] K. A. Joshi and D. G. Thakore, "A survey on moving object detection and tracking in video surveillance system," *International Journal of Soft Computing and Engineering*, vol. 2, pp. 2231-2307, 2012.
- [19] D.Mohanapriya and Dr.K.Mahesh, "A video target tracking using shadow suppression and feature extraction," *IEEE Xplore Digital Library*.
- [20] M. Happe, E. Lübbers, and M. Platzner, "A self-adaptive heterogeneous multi-core architecture for embedded real-time video object tracking," *Journal of real-time image processing*, vol. 8, pp. 95-110, 2013.

