A REVIEW ON EMERGING TRENDS IN HIGH SPEED REAL TIME OBJECT DETECTION AND TRACKING

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Abstract: Object detection and tracking is one of the most challenging dynamic areas of research due to the limitations/issues like variations in motion of object and variation in object size, occlusions, appearance variations, and illumination variations. The object tracking is the technique which is used to track object from the image or from the video. The detection of fast moving object is important in many tasks, such as video surveillance, vehicle detection, traffic monitoring,. Sports monitoring, and video surveillance. In static environment segmentation of object is not complex. In dynamic environment due to dynamic environmental conditions such as illumination changes, shadows and waving tree branches in the wind object segmentation is a difficult and significant problem that needs to be handled well for robust visual object detection. Real time high-speed vision is expected to be a very exciting field for the next research. Currently, the sensitivity of a high-speed vision system is low when working at a high frame rate. This paper reviews some emerging trends/algorithms of high speed, high resolution object detection and tracking in video processing.

IndexTerms **- Real-time high-speed vision, kernelized correlation filter, high frame-rate (HFR), Multi-layers particle filter (MLPF)**

I. INTRODUCTION

Object tracking in video has been an dynamic research area for decades. This interest is encouraged by numerous applications, such as surveillance, human-computer interaction, and sports event monitoring. In a video there are primarily two sources of information that can be used for detection and tracking of objects: visual features (e.g. color, texture and shape) and motion information. Robust approaches have been suggested by combining the statistical analysis of visual features and temporal analysis of motion information. A typical strategy may first segment a frame into a number of regions based on visual features like color and texture, subsequently merging of regions with similar motion vectors can be performed subject to certain constraints such as spatial neighborhood of the pixels. A large number of methodologies have been proposed by a number of researchers focusing on the object detection from a video sequence. Most of them make use of multiple techniques and there are combinations and intersections among different methodologies. All these make it very difficult to have a uniform classification of existing approaches.

Simple operations such as background subtraction and segmentation can hardly achieve passable results when the target is tracked under complex scenes or by a moving camera which is controlled by an actuator. As a result, complex algorithms with huge computation are used to achieve robust tracking. However, the response speeds of conventional tracking systems are limited to 30 fps due to the bottleneck of serial image data transmission and processing. Obviously, this cannot meet the needs of detecting and tracking high-speed moving object in real scenes. High-speed vision systems have two properties: 1) small displacement between frames, and 2) complex timing and limited resources for fast image processing. To realize high speed vision-based feedback control, a huge number of image frames need to be processed in real time. Unfortunately, the currently used image processing algorithms including object tracking and recognition have been designed for conventional video signals, which work at several dozen frames per second. The key idea of real-time high-speed vision based applications is to utilize the small displacement between frames for optimizing or simplifying image processing algorithms. After optimization, appropriate development environments are selected for the implementation of the improved algorithm by considering the application purpose [14]. Modern imaging sensors with higher megapixel resolution and frame rates are being increasingly used for wide-area video surveillance (VS). This has produced an accelerated demand for high-performance implementation of VS algorithms for real-time processing of high-resolution videos. The emergence of multi-core architectures and graphics processing units (GPUs) provides energy and cost-efficient platform to meet the real-time processing needs by extracting data level parallelism in such algorithms. However, the potential benefits of these architectures can only be realized by developing fine-grained parallelization strategies and algorithm innovation [3].

The recent introduction of various multi-core and GPU architectures has ushered a new era of parallel computing and are highly promising for obtaining real-time implementation of the VS algorithms. New architectures and parallelization strategies are being developed due to the increased accessibility of multicore, multi-threaded processors along with the general purpose graphics processing units (GPUs). The recent developments in the GPU architecture have provided an effective tool to handle the workload [3]. A fast and vigorous method is presented by incorporating an adaptive object detection technique within a kernelized correlation filter (KCF) framework. An adaptive object detection method is proposed to improve the location and boundary of the object when the tracking confidence value is below a certain threshold. The experiments show that KCF tracker method may not be able to perform well if there are more than one dubious salient object in a given scene or the object is too small to auto-detect and initialize our tracker [4]. A change information based moving object detection scheme is proposed. The spatio-temporal spatial segmentation result of the initial frame is obtained by edge based MRF modeling and a hybrid MAP estimation algorithm (hybrid of SA and ICM). The segmentation result of the initial frame together with some change information from other frames is used to generate an initialization for segmentation of other frames. Then, an ICM algorithm is used on that frame starting from the obtained initialization for segmentation. It is found that the proposed approach produces better segmentation results compared to those of edgeless and JSEG segmentation schemes and comparable results with edge based approach. The proposed scheme gives better accuracy and is approximately 13 times faster compared to the considered MRF based segmentation schemes for a number of video sequences.

Here, “real-time” refers to the process of image frames obtained from the image sensor being processed immediately (in a few microseconds). In addition, image features extracted from the image frames can be transferred to a control system with very little delay (of millisecond level) for rapid pattern recognition, fast feedback control, etc. Therefore, high frame-rate (HFR) real-time vision-based feedback control is difficult to achieve by using an offline high-speed vision system. To overcome the restrictions of offline high-speed vision systems, several real-time high-speed vision systems have been developed recently, which can be used as real time vision sensors working at several thousands of Hertz. In such systems, image processing algorithms are accelerated by using hardware circuits. Further, real-time high speed vision feedback control can be achieved at HFR. In Section III the recently developed high-speed real-time object detection and tracking system and integrated algorithms are discussed.

II. OVERVIEW OF MOVING OBJECT DETECTION AND TRACKING

Real time object tracking is defined as the process of approximating trajectory or path of an object in successive frames. The main goal of object tracking is the process of segmenting the interest of an object or multiple objects from the video scene and keeping track of its motion, occlusion and orientation. It is challenging and interesting task to track the object of interest using image processing techniques for various applications. Recently, image processing has become the wide area of research field. Real time object tracking system is the one of them. Some difficulties or challenges appear during the various stage of object tracking.

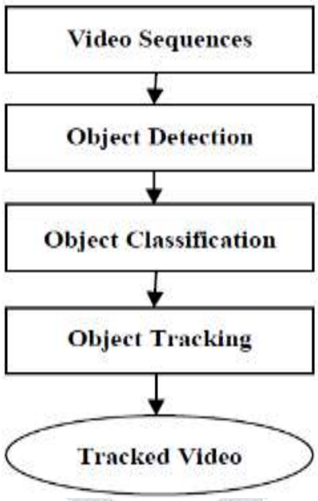

Fig. 1. Basic Block diagram of Object Tracking Stages

OBJECT DETECTION:

1. Frame Differencing:
It is a technique to check the difference between two consecutive frames. Frame differencing employs the input as two image frames of video and produces the output such as the new pixel value or difference of the pixel values that can be obtained by subtracting pixels value of second frame image from the first frame image. Method is easy and simple to implement but detection of object cannot give accurate result.

2. Optical flow:
Optical flow is a technique that presents an apparent change in the moving object’s location between frames of given video. It employs the motion field that represents the directions and velocity of each point in every frame. It takes more time to detect complex object motion and this technique is more suitable for multiple moving object detection.

3. Background Subtraction
Background subtraction method extracts the moving objects or foreground object. For that compare the reference background image to the current image and find the difference in pixel values between consecutive frames. When the difference has detected, classify that object as moving object. Performance of the background subtraction is well for static background and deals with the multiple moving objects.

OBJECT CLASSIFICATION:

1. Shape based classification

Shape information of moving object has achieved from the representation of point, box and blob. Each blob at every frame is considered for classification. Pattern matching approach can be applied. It does not perform well for dynamic condition.

2. Motion based classification

Object may be represents itself with the complex motion. To provide reliable and efficient classification, motion based classification can be used in object tracking. It does not require predefined pattern template. Using motion based classification, it is difficult to identify the non moving human.

3. Color based classification

If the image is colored image then the color based classification is applied to classify object by using the feature as color which is constant and easy to identify that particular object. For real time application, color histogram based technique is used in object tracking. It handles the occlusion of object.

4. Texture based classification

Texture is the intensity variation of the surface. It is an important characteristic for different types of object in image. Texture classification consists two phases as learning and recognition phase. Learning phase yields set of texture features for each frame of object and recognition phase compares texture feature to every frame with the best match. It improves quality of computational time for tracking process.

OBJECT TRACKING:

a. Point based tracking

It is a complex problem to track an object according to the feature points of that objects. It causes the false detection of object and occlusion of object in frames. There are various methods that use the point based tracking as below.

1) Kalman Filter:

Kalman filter is based on probability density function. It is a set of mathematical equations. So it is complex method but it gives always optimal solution. Feedback control can be estimated by using kalman filter.

2) Particle Filter:

Particle filtering creates all models for one state variable before moves to next variable. Restriction of Kalman filter is the assumption of state variable can be overwhelmed by using the particle filtering.

3) **Multiple Hypothesis Tracking**:

Multiple Hypothesis tracking is also known as iterative algorithm that begins with the set of existing track hypothesis. Object's position in every frame is made for each hypothesis. This method has capability to track multiple objects and handle occlusion problem.

b. Kernel based tracking

Kernel based tracking refers to the appearance of object and object. Kernel can be elliptical or rectangular shape. Object motion is the key feature of kernel based tracking method. The motion of object is may be in form of parametric transformation either translation, affine or rotation. Various kernel based tracking techniques are described in

1) **Simple Template Matching:**

Simple template matching is the technique to find the small region of the image that matches with the template image in each frame of given input video. This template image is considered as reference image for the next frame. After that, all possible scenarios can be calculated to know that how well the model fits the position of picture in the frames. This method has ability to track single image and handles partial occlusion.

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2) Mean Shift Method:

Mean shift method is to finding local maxima of density function from the given discrete data samples. It is a non parametric feature space analysis method. Mean shift estimates the positions of the region in the current frame from the previous frame. It is gradient ascent approach that tracked the object by use of histogram.

3) Support Vector Matching:

Support vector matching is the technique to give a set of positive and negative training values. In that, positive set of values are considered as tracked object and other remaining objects are considered as negative training values that are not tracked image object. It can be capable of handling partial occlusion but with the requirement of training and deal with the single image.

4) Layering Based Tracking:

Multiple objects can be tracked by using the layering based tracking. Each layer consists of motion like translation and rotation, shape such as ellipse and layer appearance that is based on intensity. Layering is accomplished by first compensating the background motion such that the object's motion can be estimated from the satisfied image by means of 2D parametric motion.

c. Silhouette based tracking

Silhouette based tracking is the technique that use the information encoded inside object region for tracking. Objects may have complex shape like as shoulders, finger and hand that cannot be described properly by simple geometric shapes.

For that silhouette based tracking is used to define precise shape of object. It has ability to handle occlusion, object split and combine and deal with the different various shapes of objects.

1) Contour Matching:

Contour matching select points on the boundary of object in every frame. Calculate the contour in previous frame and it's new position in current frame. Two different approaches are used for tracking. First is state space model that specify shape and motion of contour. Second approach minimizes the contour energy using direct minimization techniques like gradient descent. It is capable of dealing large variety of object shapes for tracking.

2) Shape Matching:

Shape matching is the similar technique as template matching. Detected silhouettes in each frame can be found and after that, shape matching is applied to matches the shape or silhouettes detected in two successive frames. This technique is capable of handling occlusion using Hough transform techniques and tracking single object from the given video sequences

III. RELATED WORK

Emerging Trends in High Speed object Tracking:

TCNN: Tubelets with Convolutional Neural Networks for Object Detection from Videos is proposed. The system includes works is three-folded. 1) A deep learning framework that extends popular still image detection frameworks (R-CNN and Faster R-CNN) to solve the difficulty of general object detection in videos by including temporal and contextual information from tubelets. It is called T-CNN, i.e. tubelets with convolution neural network. 2) Temporal information is effectively incorporated into the proposed detection framework by locally propagating detection results across adjacent frames as well as globally revising detection confidences along tubelets generated from tracking algorithms. 3) Contextual information is utilized to suppress detection scores of low-confidence classes based on all detection results within a video clip. However proposed framework is based on the popular still-image object detection [1]. A new algorithms for parallel processing of video object detection like Gaussians mixture model (GMM) for background modeling, morphological operations for post-processing and connected component labelling (CCL) for blob labeling have been proposed. Novel parallelization approaches and fine-grained optimization techniques are described for fully exploiting the computational capacity of CUDA cores on GPUs. Experimental results show parallel GPU implementation achieves significant speedups of ~250× for binary morphology, ~15× for GMM and ~2× for CCL when compared to sequential implementation running on Intel Xeon processor, resulting in processing of 22.3 frames per second for HD videos. The future work will include testing the current implementation on very high-resolution (20 megapixel) panoramic camera output to measure its scalability and efficacy [3].

An algorithm for fast and robust technique is proposed by incorporating an adaptive object detection technique within a kernelized correlation filter (KCF) framework. The KCF tracker is automatically initialized via salient object detection and localization. An adaptive object detection method is proposed to improve the location and boundary of the object when the tracking confidence value is below a certain threshold.

The main contributions of this work are four-fold:

The proposed approach is able to localize and generate an adaptive bounding box in real-time around the object being tracked as the object changes its shape and size. Our approach, by conjoining tracking with detection and vice versa to form a closed loop system, makes it possible to handle long-term error free tracking. The proposed approach, by using an approximate label from the tracker in the previous frames, tracks the object in subsequent frames without requiring any computationally expensive supervised training. The proposed system runs automatically, without any manual initialization, and it achieves the best performance in terms of tracking accuracy and speed. [4]. An improved particle tracking algorithm named multi-layers particle filter (MLPF). In MLPF, the particles are divided into three categories: the main particles (M-particles), the subordinate particles (S-particles) and the regenerate particles (R-particles). In the phase of resampling and state estimating, only M-particles are involved, then the R-particles are generated and considered as new S-particles in the next cycle. To a certain extent, our algorithm maintains the diversity of particles and reduces the computation time. Besides, MLPF has significant improvements on overcoming the tracing error after the sudden disappearance of the target and solving the degradation of particles. The effectiveness of our proposed algorithm through systematic experiments. Experimental results show MLPF has better tracking effect compared to the traditional particle filter (PF) when the target is moving fast and affected by light interference. In the first experiment, the running time has been reduced from 47s to 21s while the precision increased from 64% to 96%. And for the second experiment, the running time has been reduced from 237s to 121s while precision increased from 46% to 89% [6].

An improved optical flow algorithm based on the Lucas– Kanade algorithm proposed for high speed object tracking, which can control the pseudo-variable frame rate to accurately detect the optical flow for objects at various speeds. High-frame-rate (HFR) vision system that can estimate the optical flow in real time at 1000 f/s for 1024×1024 pixel images via the hardware implementation of an improved optical flow detection algorithm on a high speed vision platform [9].FPGA-based high-speed vision platforms have been developed for the hardware implementation of various types of image processing algorithms such as a gravity extraction function on an FPGA, a high-speed Hough transform processor on FPGA [58]. Qingyi Gu et al. developed a real-time optical flow system that can simultaneously estimate pixel wise optical flows of 512×512 images; the optical flow estimation was accelerated with a certain accuracy by introducing the improved method with (1) frame-straddling in calculating temporal brightness gradient It, (2) optimal pixel-interval selection in calculating spatial brightness gradients, and (3) integral image in calculating the product sums of the partial derivatives. On the GPU-based high-speed vision system, full pixel and On the GPU-based high-speed vision system, full pixel and real-time optical flow estimation was conducted for 512×512 images at 250 fps. Its effectiveness was verified by showing experimental results for fast moving objects, which involved 100 km/h or more motions [16].

High efficient processing based on pipeline processing in order to improve the processing speed of CPU and GPU in existing moving-object detection system. In our method, pipeline processing and multi-thread processing were implemented in an existing program which is a sequential processing. The average speed of 1 frame was 0.65 ms [12].

Qing-Yi Gu et. al reviewed the recent progress of a real time high-speed vision system and its applications. Currently, the sensitivity of a high-speed vision system is low when working at a high frame rate, and the resolution of the high-speed vision system is limited to 1 megapixel when working at 1 000 fps or more. We expect a new generation of image sensors with full resolution and high sensitivity. In the future, the target application fields of real-time high-speed vision will include biomedicine, micro-/nano- manipulation, infrastructure monitoring, and high-frequency object detection and tracking. [14]. Qingyi Gu et al developed an HFR color histogram-based multi-object tracking system that was capable of processing 512 X 512 images at 2,000 fps in real time based on hardware implementation of a cell-based multi-object color histogram. We plan to introduce higher order local auto-correlation features (HLACs) into our multi-object tracking system to improve its robustness based on shape recognition. On the basis of these results, we will improve our color histogram-based multi-object tracking system for three-dimensional tracking and high-speed robot control in the real world by expanding the multi-object color histogram extraction [17]. Sushil Pratap Bharati et al. presented an algorithm for fast and robust method by incorporating an adaptive object detection technique within a kernelized correlation filter (KCF) framework. Proposed method has success rate around 70 to 80 % and precision rate is around 80 % [23]. Mariya Monica.V et al. an algorithm for simultaneous tracking of the multiple objects Based on Kalman Filter and Gait Feature Extraction have been proposed. The future scope is to implement the object tracking using Raspberry Pi to enhance the speed [24].

Sunanda R. Hanchinamania et al. presented high speed background subtraction algorithm for moving object detection is proposed. The video is first converted to streams and then applied to convolution filter which removes high frequency noise components to obtain smoothened images. The smoothened images are then applied to background subtraction algorithm with adaptive threshold which gives detected object present in background image. The detected object is then applied to convolution filter to remove the spurious distorted pixels which improves the quality of image [25]. K. Saranya et al. describes the framework of the video surveillance system and provides the algorithms and implementation results of the current work on multi-person tracking. It is done by doing background subtraction and extracting the foreground object, using the extracted foreground object the object containing motion alone is detected and tracked. In future this work will be handling the occlusion problem based on assigning unique ID for each object [26]. Kai Kang et al. proposed a complete multi-stage pipeline for object detection in videos. The framework efficiently combines still-image object detection with generic object tracking for tubelet proposal. Their relationship and contributions are extensively investigated and evaluated. Based on tubelet proposals, different perturbation and scoring schemes are evaluated and analyzed. A novel temporal convolutional network is proposed to incorporate temporal consistency and shows consistent performance improvement over still-image detections [27]. Kai Kang proposed a deep learning framework that incorporates temporal and contextual information from tubelets obtained in videos, which dramatically improves the baseline performance of existing still-image detection frameworks when they are applied to videos. It is called T-CNN, i.e. tubelets with convolutional neural networks. [33] [34].

Wei Zhang et al. proposed a fast object detection method based on motion compensation. The background model of each pixel is initialized according to the first frame and is propagated to current frame by employing the edge-preserving optical flow algorithm to estimate the motion of each pixel. Each pixel can be finally classified as foreground or background pixel according to the compensated background model which is updated online by the fast random algorithm. The method is not suitable for the situation of dynamic background. Moreover, the speed of proposed method achieved 8 fps. In future works, the focus is on developing more robust moving object detection approaches in real-time way to meet other applications [36]. Tianxu Zhang et al. proposed a novel temporal-spatial variable scale algorithm (TSVSA) is presented which proposes to solve the problem of detecting multiple moving objects from complex backgrounds. The method has only considered the problem of moving object detection and analysis with a uniform linear motion in temporal 1-D and spatial 2-D domain [39]. Aziz Karamiani proposed a method based on edge features, background subtraction, and frame difference for detecting and tracking moving objects [40].

Ross Girshick proposed a Fast Region-based Convolutional Network method (Fast R-CNN) for object detection. Fast R-CNN builds on earlier work to efficiently classify object proposals using deep convolutional networks. Compared to earlier work, Fast R-CNN employs a number of innovations to improve training and testing speed while also increasing detection accuracy. Of course, there may exist yet undiscovered techniques that allow dense boxes to perform as well as sparse proposals. Such methods, if developed, may help further accelerate object detection [41]. Erik Bochinski et. Al presents IOU (intersection-over-union) tracker considerably outperforms the state-of-the-art at only a fraction of the complexity and computational cost. This becomes possible due to the recent advances in the object detection domain, not at least due to the current boom of CNN-based approaches. [45]. Su Liu et al. designed and implemented an FPGA-based object detection and tracking system which uses a background subtraction technique. The design was carried out using Verilog HDL and the implementation was based on the Altera DE3 development board. It has been studied and profiled that the object detection and tracking algorithm implemented in the software version and highly-parallel architecture is designed to achieve good throughput. As future work we plan to improve the sensitivity of the tracking algorithm to the luminance of the scene. This can be achieved by more accurate background training as well as using techniques based on hidden Markov models [48].

Congyi Lyu et. al proposed Several challenges are encountered in tracking this kind of small-size and high-speed objects; these challenges include: (1) the motion speed (up to 200km/h) of the object is extremely fast that the image captured by the camera can become easily blurred; (2) the size of the objects is small and there is not enough texture feature on the surface of the objects; (3) high-speed objects typically move in outdoor environments, which have complex backgrounds and the light conditions; and (4) a balance between robustness and real-time efficiency is difficult to achieve. The motion blurred object can be detected by applying the proposed object recognition method using multi-features (geometry features and object motion features)

[52]. Micha_l Staniszewski et al. presented survey of recent work in the area shows that current methods can be very effective in a wide range of environments and imaging conditions. However, there is still much room for improvement, especially in cases of multiple occlusions and where there are many objects in close proximity. Also, the speed of execution needed for real time tracking remains a challenge for the computationally more demanding methods. The continuing work will be devoted to a precise performance comparison among the current methods [53]. Junchul Junchul Ki et al. presented parallel processing schemes using OpenMP and SSE and CUDA programming for fast feature extraction in object recognition with autonomous mobile robots. As to the future works, we are investigating how the proposed method can be further accelerated by integrating it with CPU and GPU in searching and matching with database [54].

IV CONCLUSION AND FUTURE SCOPE

In this paper, we reviewed the emerging trends in and challenges of a real time high-speed vision system and its applications. All the major aspects of object detection and object tracking have been addressed. Various techniques/algorithms in these aspects have been explained in brief and merits and demerits were highlighted in each and every technique. Many conventional image processing algorithms can be simplified by considering the small displacement between frames of high-speed vision. Simplified algorithms can be implemented and accelerated on different platforms such as FPGA, GPU and CPU according to the need of application.The existing technique has the problem of false detection and tracking, direction of freedom, occlusion (Multi objects come together), temporal consistency, abrupt changes of illumination etc. In the existing system sensitivity of a high-speed vision system is low when working at a high frame rate. We expect a new generation of image sensors with full resolution and high sensitivity. Therefore existing system has limitations on high speed and high resolution detection at real time. Therefore to enhance the performance of detection and tracking of high frame rate, high resolution video future novel technique should be developed which can work at high speed and high resolution. Future scope is to develop effective object detection for high speed, high resolution with better performance i.e. better accuracy and sensitivity.

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